Sequential Markets, Market Power and Arbitrage

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Abstract

We develop a theoretical framework to characterize strategic behavior in sequential markets under imperfect competition and limited arbitrage. Our theory predicts that these two elements can generate a systematic price premium. We test the model predictions using microdata from the Iberian electricity market. We show that the observed price differences and firm behavior are consistent with the model. Finally, we quantify the welfare effects of arbitrage using a structural model. In our setting, we show that full arbitrage is not necessarily welfare-enhancing in the presence of market power. It reduces consumer costs but decreases productive efficiency.

Keywords: Electricity market, Market power, Wind generation, Spot market, Forward market, Structural estimation

JEL classification: L11, L94, L98, Q41, Q42

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1 Introduction

A variety of economic goods are traded through sequential markets—a set of forward and spot markets for a good such as treasury bonds, stocks, coal, electricity, natural gas, oil, and agricultural products. The rational behind establishing sequential markets comes from simple economic theory. For a commodity that has uncertainty in its delivery price or quantity, sequential markets can improve the efficiency of the final allocation. Under strong assumptions such as risk neutrality and common information, prices in sequential markets should converge in expectation (Weber, 1981). Empirical evidence is, however, usually inconsistent with this simple economic theory—in practice, prices in sequential markets often do not converge.

Previous studies provide several potential channels that explain why prices in sequential markets do not converge, such as risk aversion (Ashenfelter, 1989; McAfee and Vincent, 1993) and asymmetric shocks (Bernhardt and Scoones, 1994; Salant, 2014). However, the empirical evidence of systematic price differences often cannot be fully explained by risk aversion or asymmetric shocks.[1] In this paper, we develop a new framework to investigate this question by analyzing the role of market power in creating price deviations in sequential markets.[2] In particular, we examine how the existence of market power can interact with constraints to arbitrage, and prevent full price convergence. We then analyze the welfare implications of price arbitrage in the presence of market power. Arbitrage almost always improves welfare in a simple model with perfect competition. However, we show both theoretically and empirically that such implications can change once we take into account the existence of market power in sequential markets.

We begin by developing a simple theoretical framework to characterize the behavior of firms in sequential markets in the context of electricity markets. Given that these markets are oligopolistic, we put special emphasis on the behavior of strategic players with market power. In the simplest example, we consider two sequential markets: the forward market and the real-time market.[3] Both markets trade the same commodity, electricity, to be produced at a particular delivery time. A monopolist decides how much to sell in each market. We assume that demand is inelastic and allocated in full in the forward market. This assumption comes from the fact that market operators in electricity markets typically schedule most or all expected demand in the day-ahead market, and use subsequent markets to allow for modifications in production commitments between producers. The monopolist still faces a downward-sloping demand curve in both markets, due to

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[1]For example, Borenstein et al. (2008) show that the price differences in the forward and spot markets in the California electricity market cannot be fully explained by risk aversion, estimation risks, or transaction costs.

[2]Borenstein et al. (2008) point to market power as a channel driving price premia in the California electricity market. Our contribution is to formalize this channel in a model with limited arbitrage, as well as to test the predictions of the model more directly.

[3]In practice, there can be more than two sequential markets. For example, the Iberian electricity market in our empirical analysis has up to eight sequential markets to allocate hourly electricity production.
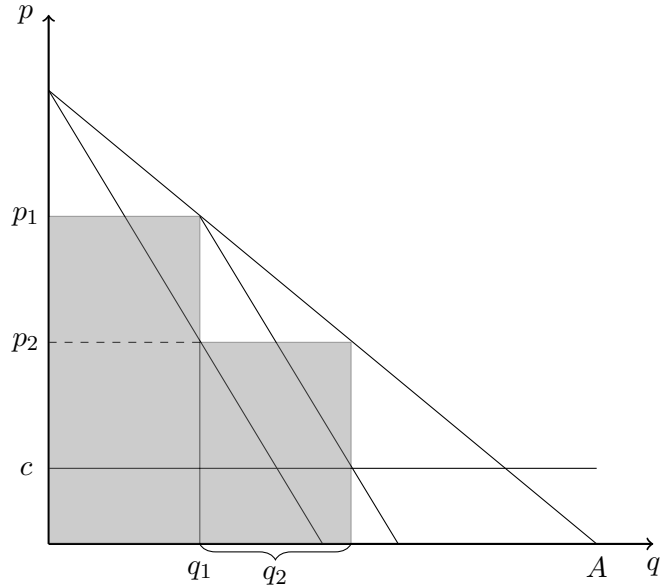
Figure 1: A Price Discriminating Residual Monopolist

This figure shows the intuition behind the declining price result (Result 1). A residual monopolist has an interest in more expensive power plants setting a high price in the first market (p_1). In the second market, the monopolist can regain some of the withheld quantity by lowering the price (p_2).

the presence of fringe suppliers, who offer production at their marginal cost.

Figure 1 provides a graphical illustration of the model. The monopolist participates in two markets. In the first market, it offers q_1 and receives p_1. In the second market, the monopolist can increase its quantity by q_2, getting p_2. The key insight is that, because q_1 has already been committed in the first market, the monopolist's strategic position changes in the second market, creating an incentive to produce more. In this simple example, the monopolist anticipates these effects and splits the quantity equally between the two markets. This equalizes the marginal revenue in the first market to the market price in the second market, which becomes the relevant opportunity cost. In the context of the broader economics literature, the regulation in this market creates something similar to a dynamic price-discriminating monopolist facing naïve consumers, leading to a declining price path analog to a dynamic monopolist facing naïve consumers (Coase, 1972). Indeed, in the presence of infinitely many sequential markets, the monopolist creates a price schedule that mimics first degree price discrimination.

An important assumption in the framework is that fringe producers offer their production at marginal cost. That is, they are not strategic, and are willing to produce as long as the price exceeds their marginal cost. However, given the equilibrium price differences between the two markets, fringe firms could arbitrage by selling more at a high price in the first market, and reducing their output in the second market. Similarly,

demand could arbitrage price differences by postponing purchase, inducing prices to converge. Why would firms not arbitrage these differences? We identify institutional constraints that make such full arbitrage difficult. In particular, bidders in the market can bid only up to the production capacity for their power plants, which limits the ability to arbitrage. Furthermore, systematic swings in scheduled production or demand are discouraged by the regulator.

Interestingly, both constraints are less binding for wind farms. First, wind farms almost never produce at their maximum capacity. Second, they have stochastic output, making departures from planned production more "justifiable" to the scrutiny of the regulator. However, do wind farms have an incentive to arbitrage price differences? We extend the framework to allow for strategic arbitrage, and show that, if price differences are driven by market power, only fringe wind farms will have an incentive to arbitrage. Dominant firms (i.e., firms that are large enough) do not have an incentive to arbitrage. In fact, our theory predicts that dominant firms will have an incentive to withhold production in the forward market, in which they exercise market power.

We test our theoretical predictions by analyzing firm behavior in the Iberian electricity market. The Iberian market provides several key advantages for testing our theoretical predictions. First, the Iberian market allocates hourly electricity production from producers to consumers using a day-ahead auction and seven subsequent intra-day auctions. This market structure allows firms to update their sales and purchase positions multiple times during a day. Second, there is ample publicly available data for the Iberian electricity market, which allow us to analyze firms' strategic behavior in sequential markets at high resolution. Third, the Iberian market consists of a few dominant firms that have 70% of the market share, as well as many competitive fringe firms, making the exercise of market power relevant. Because our data reveals firms' identities, we can investigate how dominant and fringe firms differently respond to the incentives created by the sequential markets.

Consistent with the predictions from our model, we find a systematic day-ahead price premium in the Iberian electricity market. We provide evidence that the day-ahead price premium is driven by the interaction of market power and regulatory restrictions on arbitrage. We show that the day-ahead premium correlates with strategic firms' abilities to exercise market power, such as total forecasted demand and the elasticity of residual demand, in a way that is consistent with the theoretical model. We also find strong empirical evidence that fringe wind farms systematically oversell electricity in the day-ahead market with a high market clearing price, and update their positions in later markets by purchasing electricity with a lower price, which implies that fringe wind farms engage in price arbitrage. Interestingly, we do not find such arbitrage for wind farms operated by dominant firms. Conversely, dominant firms undersell or withhold their total

electricity production in the forward markets and update their positions in the opposite way compared to fringe firms, also consistent with our theory.

The results from our empirical analysis reveal that dominant firms exercise market power and competitive fringe firms engage in price arbitrage. Is the price arbitrage welfare-improving and does more arbitrage enhance social welfare? Our theoretical model suggests that, in the presence of market power, price arbitrage may not improve social welfare, whereas it is likely to improve consumer surplus.[4] To investigate these welfare implications, we build a structural Cournot model with a forward and real-time market.[5] The model is useful to analyze the relevance of market power as a channel explaining the price premium. In the context of the Iberian electricity market, we show that this channel appears to be empirically relevant, explaining a good part of the distribution of the day-ahead premium in the data. The structural model is also useful to perform counterfactual analysis on the welfare effects of arbitrage and market power. Paralleling Allaz and Vila (1993), we empirically show the benefits of having sequential markets as a way to reduce market power. Paralleling the literature on dynamic price discrimination, we show that full arbitrage is not necessarily welfare enhancing, even if such arbitrage does not generate transaction costs.

Our findings have important take aways that can apply to other forms of sequential markets. First, our model suggests that one needs to be cautious at evaluating the benefits of price convergence between forward and spot markets, as full arbitrage does not necessarily lead to more efficient outcomes. Whereas price convergence is in itself a sign of a healthy arbitrage market, it does not always improve the final allocation. We expect this to be more likely in settings in which the second market is less distorted than the first, which in our case is driven by firms putting lower markups in the second market. Furthermore, our model emphasizes that, even under full arbitrage, asymmetric firms take different strategic positions as a function of their degree of market power. Therefore, even in well arbitraged markets, one can use sequential markets as a way to learn about the extent of market power.

Our paper relates to several literatures. First, it relates to the literature examining sequential markets and arbitrage (Allaz and Vila, 1993). Different than previous models, in our setting arbitrage is not competitive, giving raise to systematic price differences. Also different from other papers, the forwarding motives arises from the demand side, which is concentrated in the day-ahead market.[6] We present a theory in which restrictions to arbitrage combined with market power generate a declining price path, resembling the literature on durable good monopolies when consumers are not sophisticated or impatient (Coase, 1972), and clearance

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[4]As explained below, the intuition parallels the literature on dynamic price discrimination (Lazear, 1986). Arbitrage reduces the scope for price discrimination, which increases consumer surplus but increases the deadweight loss in the market.

[5]The model is a dynamic extension to the static Cournot game in Bushnell et al. (2008).

[6]In Allaz and Vila (1993), the forward motive arises purely for strategic reasons, as suppliers compete to obtain market share. In this sense, our baseline setup closely resembles a procurement auction with resale.

sales (Lazear, 1986; Nocke and Peitz, 2007). This explanation can complement other existing theories explaining the lack of price convergence in sequential markets, such as those related to risk aversion (McAfee and Vincent, 1993) or asymmetric random shocks (Bernhardt and Scoones, 1994; Salant, 2014). The paper is related to Coutinho (2013), who, using a theoretical model of supply function, shows that similar strategic effects can arise in markets for re-sale of Treasury bills. Our work complements the theoretical literature by showing that this channel is empirically relevant, directly testing predictions from the model using highly disaggregated data.

Second, our theoretical and empirical findings provide key insights into current policy discussions in energy policy. The lack of arbitrage has been documented as a central policy question in many electricity markets in the United States and other countries (Saravia, 2003; Longstaff and Wang, 2004; Borenstein et al., 2008; Hadsell, 2008; Bowden et al., 2009; Jha and Wolak, 2014; Birge et al., 2014). Our model predicts that a positive day-ahead premium can arise as a result of market power. We empirically show that this prediction is consistent with the price premium and market power observed in the Iberian electricity market. The model's prediction is also consistent with the price premiums found in the literature for other electricity markets including the California, Midwest, New England, New York, and PJM markets.[7] Finally, different from previous work, we emphasize that full arbitrage of price differences is not necessarily welfare-enhancing under imperfect competition. This finding can be a useful insight into the ongoing discussion about whether regulators in electricity markets should seek full arbitrage through virtual bidding or speculators, given the fact that most electricity markets are believed to have some degree of imperfect competition.

In addition, our empirical analysis provides a framework to exploit sequential markets to measure market power. Our approach leverages the nature of sequential markets to examine how dominant firms and competitive fringe firms take strategic advantage of sequential markets. We show that fringe and dominant wind farms behave very differently in sequential markets as a result of market power. Comparing bidding strategies between wind producers provides some advantages as, to first order, a wind farm's output is exogenously given by weather patterns.[8]

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[7]Similar to our empirical findings in the Iberian electricity market, the literature finds *positive* day-ahead price premiums in many electricity markets, including the New York market (Saravia, 2003), the PJM market (Longstaff and Wang, 2004), the New England market (Hadsell, 2008), and the Midwest market (Bowden et al., 2009) for most hours. For the California market, Borenstein et al. (2008) find statistically significant *negative* day-ahead price premiums for part of their sample periods. However, they also document evidence of monopsony power during this period that was exercised by buyers in the market. Some of these studies also provide potential explanations for the observed price differences. For example, Saravia (2003) describes that regulatory constrains in the New York electricity market may have created firm behavior that is similar to a price discriminating monopolist.

[8]There is an extensive literature that estimates market power in electricity markets. For example, see Wolfram (1998, 1999); Borenstein et al. (2002); Kim and Knittel (2006); Puller (2007); Bushnell et al. (2008); McRae and Wolak (2009); Reguant (2014). To estimate market power, most papers estimate power plants' marginal costs based on input costs and the engineering estimates of technology parameters. Bidding strategies from wind farms provide a good comparison group, as the marginal cost of production is essentially zero and their final production is almost entirely driven by exogenous weather conditions, regardless of their owner

The paper proceeds as follows. In Section 2, we describe a model of sequential markets with market power under alternative forms of arbitrage. In Section 3, we explain the institutional details and data. Section 4 shows how the price differences observed in the data appear to be related to measures of market power, and how fringe and dominant firms behave very differently in the market, in a way that is consistent with the theoretical framework. Section 5 presents a structural model of sequential markets and analyses the effects of arbitrage. Section 6 concludes.

2 Model

In this section, we develop a model of sequential markets. Several aspects of firms' behavior can affect prices in sequential markets, such as information updating or risk aversion, among others. For simplicity, and given that our main focus is on the role of market power, we consider a setting in which there is no private information or common uncertainty.[9]

2.1 Sequential Markets

Consider a simple model in which a residual monopolist is deciding production in two stages. The problem of the monopolist is to decide how much commitment to take at the first market (forward or day-ahead market) at a price p_1, and how much to adjust its commitment in the second market (real-time market) at a price p_2. Final production is determined by the sum of commitments in each market.

Residual Demand   Residual demand in the first market (day-ahead) is given by,

$$D_1(p_1) = A - b_1 p_1. \tag{1}$$

A represents the total forecasted demand, which is planned for and cleared in the day-ahead market.[10] Whereas demand is inelastically planned for, the monopolist faces a residual demand with slope b_1. One micro-foundation is that residual demand is the inelastic demand A minus the willingness to produce by fringe suppliers, who are willing to produce with their power plants as long as p_1 is above their marginal cost, $c^{fringe}(q) = q/b_1$.

In the second market (real-time), commitments to produce A can be updated. Therefore, it is a secondary

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types such as fringe firms and dominant firms.

[9]We extend the model to allow for common uncertainty in the counterfactual experiments in Section 5.

[10]An elastic demand can be easily included by modeling demand as $A - \alpha_1 p_1$.

market for reshuffling. We assume that the residual demand in the second market is given by,

$$D_2(p_1, p_2) = b_2(p_1 - p_2). \tag{2}$$

This residual demand implies that fringe suppliers only produce more if p_2 is higher than p_1, and produce less otherwise. Consequently, the monopolist increases its quantity in the second market ($D_2 > 0$) as long as $p_1 > p_2$. For the special case of $b_1 = b_2$, this residual demand implies that fringe suppliers are willing to move along their original supply curve. In the context of electricity markets, we assume that $b_2 \leq b_1$, as production tends to be less flexible in the real-time market.[11]

Monopolist Problem   The monopolist maximizes profits by backward induction. At the second market, p_1 and q_1 have already been realized. The monopolist's problem is,

$$\max_{p_2} \quad p_2 q_2 - C(q_1 + q_2), \tag{3}$$

$$\text{s.t.} \quad q_2 = D_2(p_1, p_2),$$

$$q_1 = D_1(p_1).$$

The solution to the last stage gives an implicit solution to p_2 and q_2. In the first stage, the monopolist takes into account both periods. By backward induction, q_2 and p_2 are now a function of p_1,

$$\max_{p_1} \quad p_1 q_1 + p_2(p_1) q_2(p_1) - C(q_1 + q_2(p_1)), \tag{4}$$

$$\text{s.t.} \quad q_1 = D_1(p_1).$$

To gain intuition, we consider the results for a simplified example with linear residual demand and constant marginal costs, $C(q) = cq$.[12] Result 1 summarizes some useful comparative statics.

Result 1. *Assume that the monopolist is a net seller in this market (i.e., $q_2 > 0$). Then,*

- $p_1 > p_2 > c$;

- $p_1 - p_2$ *is increasing in A, decreasing in b_1, and increasing in b_2;*

- *if $b_2 = b_1$, $q_1 = q_2$;*

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[11]Empirically, we find that b_1 tends to be larger than b_2 by a factor of 5 to 10. Hortaçsu and Puller (2008) find evidence that the supply curve of fringe suppliers is relatively inelastic at the real-time market, which could be explained by a lack of sophistication or adjustment and participation costs.

[12]We provide a full derivation of equilibrium prices and quantities, as well as proofs of the results, in the appendix.

- *If $b_2 < b_1$, $q_1 > q_2$.*

In equilibrium, the monopolist exercises market power in both markets. However, in the second market, its position in the first market is already sunk. Therefore, it has an incentive to produce some more quantity, whereby lowering the price. The monopolist withholds quantity in the first market, and then increases its commitments in the second market, gaining back some more market share.

The results of a day-ahead price premium are analogous to those in the literature considering a monopolist engaging in dynamic price discrimination when facing naïve consumers. In the first stage, the monopolist benefits from selling the good to a set of consumers with high willingness to pay, while in the second stage, it sells the good to consumers with lower valuations. Figure 1 provides the intuition behind this result.

It is important to note that this simplified example has been presented under the assumption that the monopolist is a net seller. Under the alternative assumption that the monopolist is a net buyer (i.e., a monopsonist), the results are reversed: in the absence of arbitrageurs, or in the presence of limits on arbitrage, there would be a real-time premium, i.e., $p_2 > p_1$.[13]

Arbitrage In our example, we have assumed that demand is not elastic and, by construction, is all planned for already in the first market (A). This is motivated by the fact that the electricity day-ahead market is intended to plan for all (or most) forecasted demand. The downward slopping residual demand comes from the presence of fringe suppliers, which are bidding at their marginal cost.

In equilibrium, fringe suppliers sell more in the first market at a better price, and then reduce their commitments in the real-time market at lower prices, making some profit. However, the equilibrium leaves room for further arbitrage. Given that $p_1 > p_2$, competitive fringe suppliers could oversell even more at the first market. In such case, fringe suppliers would need to offer production below marginal cost, and then trade back those commitments. The residual demand would no longer be given by total demand minus the marginal cost curve of fringe producers.

We consider the case in which fringe suppliers compete for these arbitrage opportunities until $p_1 = p_2$.[14] Abstracting from changes in the slope of the residual demands (b_1, b_2), consider an arbitrageur that can shift the residual demand at the forward market, by financially taking a position to sell, and buy back the same quantity at the real-time market, so that $D_1 = A - b_1 p_1 - s$, and $D_2 = b_2(p_1 - p_2) + s$.[15] An arbitrageur can

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[13]In the context of the California electricity market, Borenstein et al. (2008) find evidence in support of monopsony power.

[14]An alternative interpretation is that the demand side could arbitrage by waiting until the second period. We emphasize supplier incentives because, empirically, it is where we see most of the arbitrage.

[15]Virtual bidders in markets such as MISO and California engage in these type of commitments, which, contrary to our empirical application, are allowed in those markets.

sell a quantity s in the first market, and buy it back in the second market.[16] The modified residual demands become,

$$D_1(p_1, p_2, s) = A - b_1 p_1 - s, \tag{5}$$

$$D_2(p_1, p_2, s) = b_2(p_2 - p_1) + s. \tag{6}$$

Note that this formulation is analogue to demand not clearing in full in the first market. The effective demand in the first market is $A - s$, while s is added to the residual demand in the second market.

If the costs of arbitraging are relatively small and the arbitrageurs market is competitive, s increases until p_1 converges to p_2. Therefore, the arbitrage quantity is determined with a no arbitrage condition.

Result 2. *Assume that the monopolist is a net seller and arbitrageurs are competitive so that, in equilibrium, s is such that $p_1 = p_2$. Then,*

- *$p_1 = p_2 > c$;*

- *q_1 decreases with s and q_2 increases with s;*

- *p_1 is decreasing in s and p_2 is increasing in s;*

- *s reduces total output by the monopolist.*

One important insight that arises from this result is that competitive arbitrage in this market does not lead to competitive prices. The rational for this result is that the monopolist is still required to produce the output after all sequential markets close. The arbitrageurs are only engaging in financial arbitrage, but do not produce s.

Exogenous Limited Arbitrage   In practice, s might not be chosen to equalize prices, e.g., due to some institutional constraints or transaction costs. In electricity markets, it is common to limit participation to agents that have production assets. An arbitrageur cannot take a purely financial position in the market unless it is "backed up" by an actual power plant. Another institutional feature that limits the amount of arbitrage is the fact that large swings in scheduled production, unless justified by technical operations, are typically discouraged by the regulator.

We introduce arbitrage constraints on fringe suppliers, by introducing an exogenous limit K on s.

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[16]Because we do not restrict s to be positive, the arbitrageur could be effectively selling at the first market and buying back at the second market. In equilibrium, however, $s > 0$.

Result 3. *Assume that arbitrageurs are limited in their amount of arbitrage, i.e. $s \leq K$. Then,*

- *whenever the arbitrage capacity is binding, i.e. $s = K$,, then $p_1 > p_2$;*

- *price differences are more likely to arise when K is lower, all else equal;*

- *price differences are more likely to arise when A and b_2 are larger, and when b_1 is lower, all else equal;*

- *$p_1 - p_2$ is increasing in A, decreasing in b_1, and increasing in b_2.*

The results shows that, even if arbitrageurs can bid up to their capacity, there might be price premia whenever arbitrageurs are capacity constrained. In such case, the comparative statics are similar to the case without arbitrage, and the price premia is larger when market conditions are more extreme, e.g., when demand is large or the fringe supply is less elastic.

Endogenous Limited Arbitrage   Limited arbitrage can arise endogenously due to limited competition on the arbitrageur side. We consider the presence of a single arbitrageur, who has an incentive to arbitrage price differences, but not to close the gap completely. In our setting, and given the limitations to arbitrage in the market, we interpret this special case as representing a scenario in which a limited set of players can engage in price arbitrage. The profits of the arbitrageur are given by $(p_1 - p_2)s$.

We calculate the sequential Cournot equilibrium between the monopolist producer (q_1, q_2) and the strategic arbitrageur (s). In the first stage, they choose q_1 and s simultaneously, in the second stage, the monopolist can adjust to q_2.

Result 4. *Assume that there is a single firm which has the ability to arbitrage, and maximizes profits. Then,*

- *$p_1 > p_2 > c$;*

- *$p_1 - p_2$ is increasing in A, decreasing in b_1, and increasing in b_2;*

- *$p_1 - p_2$ are smaller than in the absence of strategic arbitrage, i.e., $s > 0$.*

In the presence of a strategic arbitrageur, the main predictions of the model hold. The price premium is larger when demand is large, fringe suppliers submit inelastic supplies, and when the real-time market is more elastic.

2.2 Relative Size and Incentives to Arbitrage

In practice, arbitrage is performed by firms that also produce in the market. We consider a situation in which there are two firms, one which is large and sells substantial amounts of output, and one which is small. Both of them have the ability to engage in strategic withholding or arbitrage. For the purposes of the empirical exercise, it is useful to think about the large firm as one with several types of production (e.g., coal, gas, nuclear, wind), and the small producer as one with wind farms.

We model the large firm as the monopolist in the above examples, with constant marginal cost c. We assume that the marginal cost of the monopolist is low enough that it becomes a large player in equilibrium. For the small firm, we assume that it behaves as the strategic arbitrageur in the previous example, with the main difference that, on top of getting profits from arbitrage, it also gets profits from wind output. The profit function becomes $p_1 q^w + (p_1 - p_2)s$, where q^w is the farm's wind output, which is exogenously given by weather patterns, e.g. wind speed and direction.[17]

The presence of wind output attenuates the incentives of the arbitrageur to bring p_1 down. If the wind farm is small enough, it still has a net incentive to arbitrage and increase its profits by overselling in the first markets, i.e., setting $s > 0$. However, if the quantity produced by the wind farm is large enough, the arbitrageur does no longer have an incentive to arbitrage, and behaves in line with the monopolist, driving a price premium. Result 5 summarizes the comparative statics.

Result 5. *Assume that there is a single firm which has the ability to arbitrage, who also owns wind farms, and maximizes profits. Then,*

- $p_1 > p_2$;

- $p_1 - p_2$ *is increasing in A and q^w, decreasing in b_1, and increasing in b_2 as long as $q^w < \tilde{q}^w$;*

- $s > 0$ *as long as $q^w < \underline{q}^w$, otherwise $s \leq 0$;*

- $q_2 > 0$ *as long as $q^w < \overline{q}^w$.*[18]

Under this scenario, a price premium still arises. If the wind farm is small, it has an incentive to arbitrage price differences, i.e., $s > 0$. However, if the wind farm is large enough, then it has no incentive to arbitrage. In fact, it may have an incentive to undersell in the first market, i.e., $s < 0$. The monopolist, on the contrary, does not arbitrage the price differences away as long as it is large relative to the other player. If

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[17]Similar insights arise with the second firm choosing quantity endogenously, but just being smaller in size due to other factors, e.g. due to capacity constraints or higher marginal costs.

[18]In particular, $\tilde{q}^w \equiv \frac{(5b_1^2 + 2b_1 b_2 + b_2^2)(A - b_1 c)}{17b_1^2 - 6b_1 b_2 + b_2^2}$, $\underline{q}^w \equiv b_1 \frac{A - b_1 c}{5b_1 - b_2}$, and $\overline{q}^w \equiv \frac{(3b_1 + b_2)(A - b_1 c)}{7b_1 - b_2}$, with $\underline{q}^w \leq \tilde{q}^w \leq \overline{q}^w$, see appendix.

the monopolist became small enough relative to the wind producer, the roles could eventually revert. The monopolist would behave as an arbitrageur ($q_2 \leq 0$), while the wind farm would create the price premium. For an intermediate range of wind output $q^w \in [\underline{q}^w, \overline{q}^w]$, both strategic players have aligned incentives to increase the premium, i.e., $s < 0$ and $q_2 > 0$. In all cases, $p_1 > p_2$.

Results 1-5 describe the behavior of a strategic firm under alternative assumptions regarding the extent and nature of arbitrage. However, they share important predictions. In particular, a price premium arises as long as arbitrage is not full. Furthermore, in all equilibria the largest firm has an incentive to withhold output in the first market, and increase its commitments in the second one. We explore these testable implications in the empirical section. Before we proceed to our empirical analysis, we give some more institutional details on how sequential markets are organized in our particular application, the Iberian electricity market.

3 Institutions and Data

A deregulated electricity market usually consists of a day-ahead forward market and a real-time spot market. Most energy production is first allocated in the day-ahead market. The real-time market is used to ensure the balance between scheduled demand and supply. In this paper, we leverage the unique market structure of the Iberian electricity market, which consists of several sequential markets during a day, to study strategic behavior in these markets.[19] We begin by providing institutional details on how the sequential markets are organized. We then explain what features of a typical deregulated electricity market restrict full arbitrage between the forward market and the spot market. Finally, we describe the data used for our empirical analysis.

3.1 Sequential Markets in the Iberian Electricity Market

The Iberian electricity market is organized in a centralized fashion, with a day-ahead market and up to seven intra-day (real-time) markets. Figure 2 shows how the sequential markets are structured. In the day-ahead market (day $t - 1$), producers and consumers submit their supply and demand bids for each of the 24 hours of delivery day t, and production for each hour is auctioned simultaneously using a uniform rule, setting a marginal price of electricity for each hour of the day.[20] The day-ahead plans for roughly all expected electricity, whereas sequential markets allow for re-trading.[21] After the clearance of the day-ahead market,

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[19]The Iberian electricity market encompasses both the Spanish and Portuguese electricity markets, and was created in July 2007.

[20]In reality, the auction takes the form of a modified uniform auction, as explained in Reguant (2014).

[21]In terms of volume, roughly 80 percent of the electricity that is traded in the centralized market is sold through this day-ahead market. Firms can also have bilateral contracts in addition to their transactions in the centralized market. We observe bilateral
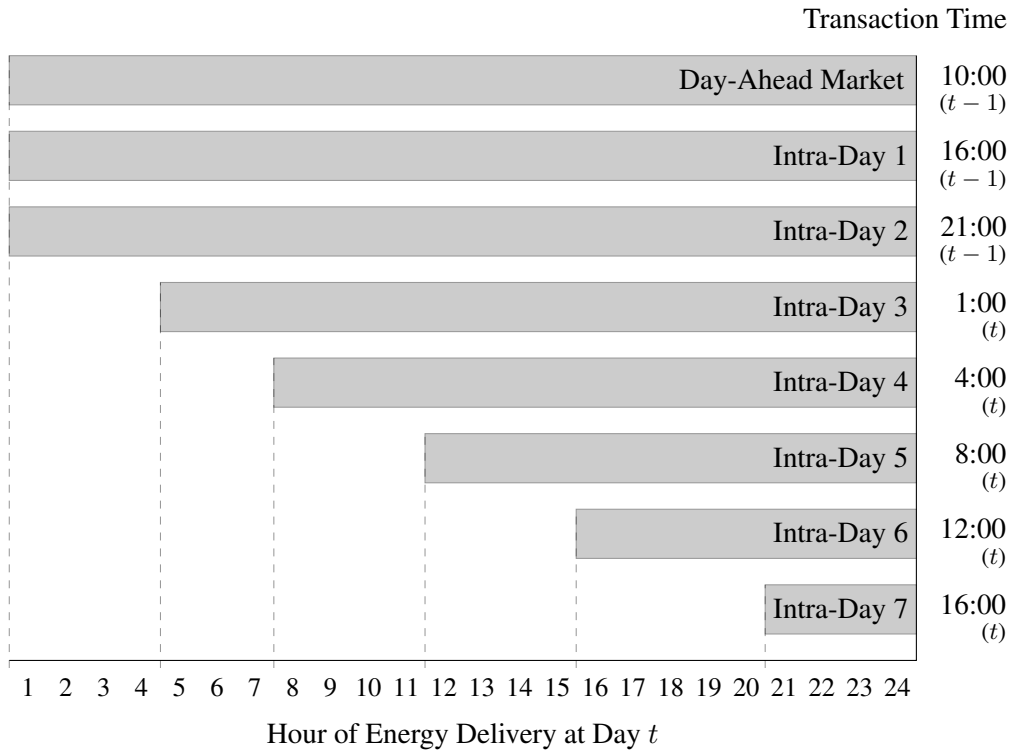
Figure 2: Sequential Markets in the Iberian Electricity Market

This figure describes the timeline of sequential markets in the Iberian Electricity Market. For a given hour of their production, firms can bid in the day-ahead market and multiple intra-day markets. The position in the last market for a given hour represents their final physical commitment to produce electricity. For example, at noon firms can change their commitments until the 5th intra-day market. Their position at the 5th intra-day market determines the amount of electricity that they are expected to produce.

the system operator checks congestion in the electricity grid. In the presence of congestion, the system operator may require some changes in the initial commitments, re-adjusting the position of several units based on their willingness to re-adjust.[22]

After the congestion market, the first intra-day market opens, still on day $t-1$. In the first intra-day market, producers and consumers can bid for each of the 24 hours of day t to change their scheduled production from the day-ahead market. For example, if suppliers want to reduce their commitments to produce, they can purchase electricity in the intra-day market. Likewise, if firms want to produce more than the assigned quantity, they can sell more electricity in the intra-day market. This means that an electricity supplier can become a net seller or buyer in the intra-day market. After the first intra-day market, firms have additional opportunities to update their positions through subsequent intra-day markets as shown in the figure. In each of the intra-day markets, the market clearing price is determined by a set of simultaneous uniform price auctions for each delivery hour.

Sequential markets allow firms to adjust their scheduled production multiple times. For example, consider a firm that wants to deliver electricity for 9 pm on day t. The firm first participates in the day-ahead market at 10 am on the day before production (day $t-1$). After realizing the auction outcome of the day-ahead market, the firm can update their position by purchasing or selling electricity in the subsequent seven intra-day markets. The final intra-day market—the 7th intra-day market—closes at 4 pm on day t. Note that the number of sequential markets available for the firm is different depending on the hour of energy delivery. For example, the firms has only three markets for their production hours from 1 am to 4 am, while the firm has four markets for hours from 5 am to 7 am.

Firms have no more opportunities to change their scheduled quantity after the final market. If their actual production deviates from the final commitment, they have to pay a price for the deviation. The market operator determines the deviation price as a function of the imbalance between the market-level demand and supply for the hour, and the willingness to adjust by other participants. We find that firms in general minimize their final deviations in response to deviation prices. We therefore do not focus on this aspect and assume that firms have appropriate incentives to minimize the deviation between the scheduled and actual production in the final market.

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contracts in our data.

[22]Whereas the congestion market is not the focus of this paper, we will take into account its presence when performing the empirical exercise.

3.2 Restrictions to Arbitrage

In the theoretical framework, we highlight that the potential lack of arbitrage is a key institutional feature in electricity markets.[23] There are a few features that restrict arbitrage in the Iberian market. First, virtual bidding is not allowed. Virtual bidders, also called financial bidders or pure arbitrageurs, refer to those agents that have neither physical generation capacity nor physical demand for electricity. While some electricity markets recently started to allow virtual bidding, it is still prohibited in many electricity markets, including the Iberian electricity market. This restriction implies that a supply bid has to be tied to a specific generation unit, and a demand bid has to be tied to a specific location for demand.[24]

Second, generation firms are not allowed to sell a quantity higher than their generation capacity. This rule limits their ability to sell electricity short. In particular, if firms intend to use most of their full generation capacity to produce electricity, this rule implies that such firms have a very limited ability to sell electricity short. Similarly, generation firms cannot purchase electricity in intra-day markets if their net production reaches zero. This rule limits their ability to purchase electricity in a market with lower expected price. Whereas firms can have unused power plants to arbitrage, systematic differences between day-ahead quantities and final quantities have at times been scrutinized by regulators, specially if those changes are not marginal. The fear for such investigation can be an additional feature that restricts firms from engaging in arbitrage.[25]

Finally, the system operator clears roughly all forecasted demand in the day-ahead market, to plan for how the electricity will flow through the grid and prepare for potential contingencies. This rule limits the arbitrage ability for the demand side. Even though demand can engage in some arbitrage, the system operator tries to plan for all expected consumption, sometimes by means of proxy bids that make up for the "missing" demand in the day-ahead market.

3.3 Wind Presence and Arbitrage Ability

Given these explicit and implicit restrictions on arbitrage, we highlight that wind generation may have potential advantages in arbitrage. First, wind farms almost never use their maximum capacity because wind

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[23]See Borenstein et al. (2008) for a description of similar issues in the context of California.

[24]For example, the New York electricity market started to allow virtual bidding in November 7, 2001 (Saravia, 2003) and the California electricity market recently started to allow virtual bidding (Jha and Wolak, 2014). Although economists are usually in favor of introducing virtual bidding, system operators in many electricity markets are often hesitant about its implementation. They are often concerned that virtual bidding may create large uncertainty in the final deliveries of electricity, which affects the system reliabitlity.

[25]For example, during the implementation of the RD 3/2006, the regulator imposed some constraints on day-ahead market prices, but not intra-day prices. Firms reacted by massively withholding either supply or demand from the day-ahead market, and clearing a substantial amount of net power in the intra-day markets. Both supply and demand withholding was investigated by the monitoring agency, and effectively sopped shortly after.

does not blow all the time. On average, they use about one thirds of their installed capacity. This means that they have greater abilities to sell electricity short in a lower-priced market. Second, wind generation faces less regulatory scrutiny for engaging in arbitrage because of the inherent uncertain nature of its production. For example, if thermal plants, which have much less uncertainty in production, engage in systematic arbitrage, regulators easily find the systematic behavior and potentially result in regulatory scrutiny. Wind generation, however, has large uncertainty in production, and therefore, it is harder for regulators to judge whether their selling and buying behavior comes from the uncertainty or from profitable arbitrage.

In our data, we find that wind generation systematically deviates from expected wind forecast, in a way that cannot be rationalized due to the distribution of uncertainty in the market. While these substantial departures have been recently noticed in many electricity markets including U.S. electricity markets, the Iberian market provides a few advantages for our empirical analysis. First, we can obtain micro data on electricity production, generation costs, and bidding behavior at the plant level. Second, the Iberian market also provides the unique market structure that is described in the previous section. Finally, wind generation is growing significantly in Spain. The total installed wind capacity was only 713 MW in 1998. It grew to 22,785 MW in 2012. As of 2012, Spain is the fourth country in terms of installed wind capacity, only after the United States, Germany and China. Wind energy was the system's third technology in 2012, with a generation of 48,156 GWh, and a cover of the electrical demand of 17.4 percent. The Iberian case therefore provides a particularly advantageous research setting to study a market with a large presence of wind production, which is likely to be a key new feature for many electricity markets in the near future.

3.4 Data

We construct a dataset using publicly available data from the market operator, Operador del Mercado Ibérico de Energía (OMIE), and the system operator, Red Eléctrica de España (REE), of the Iberian electricity market. Our dataset comes from three main sources.

The first dataset is the bidding data from the day-ahead and intra-day markets. On a daily basis, electricity producers submit 24 hourly supply functions specifying the minimum price at which they are willing to produce a given amount of electricity at a given hour of the following day. Similarly, retailers and large electricity consumers submit 24 hourly demand functions specifying the price-quantity pairs at which they are willing to purchase electricity. The market operator orders the individual bids to construct the aggregate supply and demand functions for every hour, and the intersection of these two curves determines the market clearing price and quantities allocated to each bidder. Sellers (buyers) receive (pay) the market clearing price times their sales (purchases). Accordingly, for each of the 24 hours of the days in the sample, we

observe the price-quantity pairs submitted by each firm for each of their power plants. We also observe all the price-quantity pairs submitted by the buyers. Importantly, we observe each bidding unit's curves both at the day-ahead and the intra-day markets. For each of the bidding units, we know whether their identity and type (buyers, traditional power producers (thermal, hydro) or "special regime" producers, such as renewable production, biomass, cogeneration).

The second dataset includes planning and production outcomes from the system operator. These system operator data include market clearing prices, aggregate demand and supply from each type of generation, demand forecast, wind forecast, and weather forecasts. The dataset also includes production commitments at each sequential market at the unit level. One advantage of the system operator data is that we can separate production commitments from wind, solar and other renewable technologies, whereas in the bidding data these units are often aggregated into a single bidding entity, due to their smaller size. One limitation of the system operator data, however, is that it comes from the Spanish system operator, and therefore it does not include Portuguese production units. Our results are very similar whether we focus on the Spanish electricity market (using these more detailed operational data), or the Iberian electricity market as a whole (using only bidding data).

The third dataset, which is particularly important for our welfare counterfactual analysis, includes plant characteristics, such as generation capacity, type of fuel, thermal rates, age, and location, for conventional power plants (nuclear, coal and gas). Combining these data with fuel cost data, we can obtain reasonable estimates of the marginal cost of production at the unit level. We also obtain CO_2 emissions prices and emissions rates at the plant level. As shown in Fabra and Reguant (2014), firms in the Spanish electricity markets fully internalize emissions costs. Therefore, we add them to the unit level marginal costs.

We use data from January 2010 until December 2012. During this period, the four largest generating firms were Iberdrola, Endesa, EDP, and Gas Natural. Their generation market share was on average 68 percent during this period (22%, 19%, 13%, and ,11% respectively).[26] These firms own a variety of power plants from thermal plants to wind farms. In the empirical analysis, we define these four largest firms as *dominant firms*. The market also includes many new entrants that own wind farms or new combined cycle plants. We define them as *fringe firms*.

Table 1 shows the summary statistics of the bidding data and market outcomes, where each variable is associated to its closest analogue in the theoretical model. There are 26,304 hour-day observations in the sample, with an average market price of 44.7€/MWh in the day-ahead forward market and 43.8€/MWh in the spot market. On average, there is a day-ahead market premium by 0.9€/MWh. Whereas the premium is

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[26]Figure C.1 in the appendix shows the evolution of their market shares over the sample.

not large on average, there is substantial heterogeneity across days and hours, as discussed below. The table also reports the slopes of the residual demand curves that are used in the following sections. The slope is systematically larger for the day-ahead market, as the day-ahead market tends to be have more participants. This does not necessarily mean that the day-ahead market is strategically more elastic, as firms tend to sell larger amounts of energy in such market. Indeed, the markup calculations in the table show that the implied strategic markups are larger in the day-ahead market, which is consistent with our theoretical framework.[27] Finally, the average forecasted wind production is 5.0 GWh, being on average approximately 17 percent of total demand.

[Table 1]

4 Evidence of Market Power and Arbitrage

In the theory section, we developed a model that characterizes how market power, arbitrage, and constraints for arbitragers influence market equilibrium prices in sequential markets. In this section, we provide empirical evidence for these theoretical predictions by analyzing firm behavior in the Iberian wholesale electricity market.

4.1 Forward-Market Price Premium and Market Power

We begin by documenting systematic forward market price premiums in the Iberian wholesale electricity market. Our theory predicts that a forward-market price premium could emerge if a net-seller firm has market power and market participants have limited arbitrage abilities. This prediction is consistent with the forward price premium observed in the Iberian wholesale electricity market.[28] Figure 3 shows average market prices (Euro/MWh) for each of the eight sequential markets (the day-ahead market and seven intra-day markets), in which the horizontal axis shows hours for electricity delivery. The figure indicates that there is a systematic positive day-ahead price premium—the day-ahead prices are higher than intra-day market prices. The prices also appear to be declining in time. This is particularly true for the last intra-day market. For example, see prices for hours 12 to 15. The fifth intra-day market has a particularly lower price than the prices in the other markets for the same hours.

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[27]The markup definition arises naturally from a bidding model in which $p = c + \frac{dp}{dq_i} q_i$ (Wolak, 2000).

[28]Our theory is also consistent with empirical evidence of price premiums in the U.S. electricity markets documented by previous studies. For example, Saravia (2003) documents a forward-market price premium in the New York electricity market, which is similar to our finding in the Iberian electricity market. Borenstein et al. (2008) and Jha and Wolak (2014) find a spot-market price premium in the California electricity market, which is still consistent with our theoretical prediction because monopsony power is likely to be an important factor for the price premium in the California market, as documented by Borenstein et al. (2008).
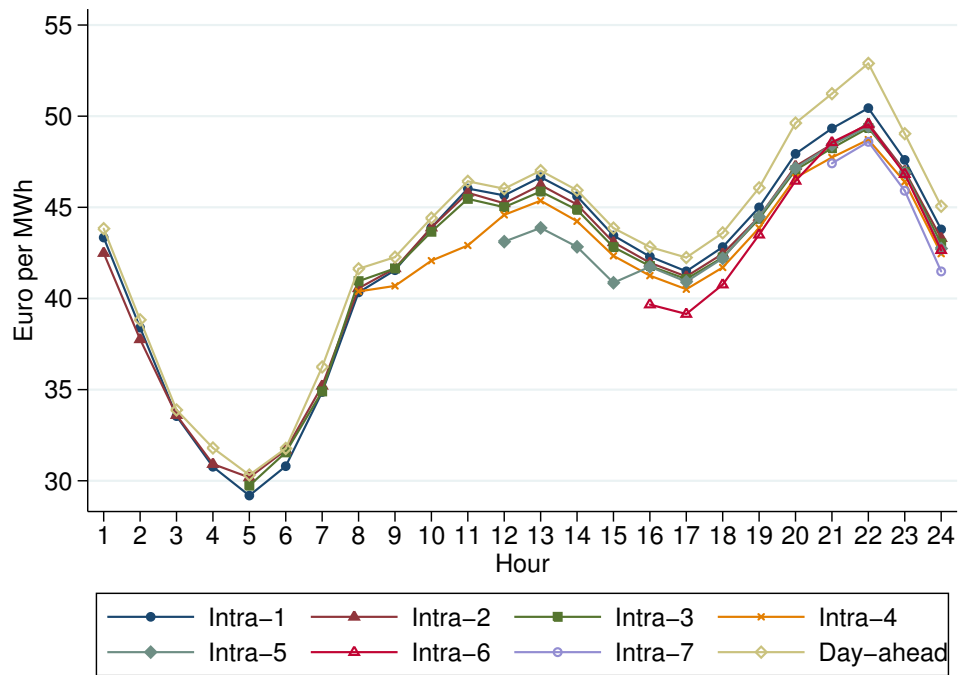
Figure 3: Market Clearing Price in the Day-ahead and Intra-day Markets

This figure shows the average market clearing price (Euro per MWh) in the day-ahead and intra-day markets, in which the horizontal axis shows hours for electricity delivery. Day-ahead market tends to exhibit prices that are on average larger than in the subsequent sequential markets.

In addition to the average market prices presented in this figure, we provide the 25th, 50th, and 75th percentiles of the day-ahead price premium in Table 2. The table suggests that the positive average day-ahead price premium in the figure is not an artifact of some price outliers. The evidence is particularly strong for the afternoon and evening hours, in which the median day-ahead price premium is above 1 Euro/MWh across the sequential markets. For hours after the midnight, the median day-ahead premium is zero, but the distribution of the price premium is systematically shifted to the right, still giving a positive day-ahead premium on average. Table 2 also suggests that the day-ahead price premium has substantial variation across days and hours. The median of the price premium differs substantially across hours, and there is large dispersion between the 25th and 75th percentiles for a given hour and market.

[Table 2]

Our theory indicates that several key factors can influence the price premium. For example, Result 3 predicts that the day-ahead price premium would be increasing in demand A, decreasing in the slope of the residual demand in the day-ahead market b_1, increasing in the slope of the residual demand in the intra-day market b_2, and decreasing in the arbitragers' arbitrage capacity K, if the price premium is driven by market power and limited arbitrage abilities as the theory predicts.[29] An important advantage of our micro-level bidding data is that we can directly calculate the values of b_{1j} and b_{2j} for each strategic firm j from our bid data because we observe each bidder's bids for each market for each hour. For each strategic firm j at hour h on day t, we calculate the slopes of the residual demand curves b_{1jht} and b_{2jht} by using the observed bids from all market participants. We calculate the residual demand and slopes for each of the four strategic firms: Iberdrola (IBEG), Endesa (ENDG), Gas Natural Fenosa (GASN), and EDP/HC (HCENE). We calculate these slopes at prices around the market clearing prices.[30] We then test our theoretical predictions by estimating an OLS regression:

$$\Delta \ln p_{ht} = \alpha + \beta A_{ht} + \gamma_1 b_{1jht} + \gamma_2 b_{2jht} + \phi X_{jht} + u_{jht} \tag{7}$$

where $\Delta \ln p_{ht}$ is the day-ahead price premium in log for hour h on day t, A_{ht} is the day-ahead demand forecast in log, b_{1jht} and b_{2jht} are the slopes of residual demand curves in log for strategic firm j for the day-ahead market and for the first intra-day market.[31] The parameters of interest, β, γ_1, and γ_2, describe

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[29]The arbitragers' arbitrage capacity K includes their explicit capacity constraint or an implicit constraint on arbitrage. For example, in theory, wind farms can oversell up to their maximum capacity in a forward market, but such levels of overselling can be hard to be justified by regulators.

[30]More concretely, we use cubic splines with knots at $\{0, 10, 20, 30, 40, 50, 60, 70, 90\}$ €/MWh to fit the residual demand curve for each firm, hour and day, and differentiate it at the clearing price to get the slope.

[31]More precisely, we define the price premium Δp_h by the difference between the natural log of the day-ahead price and the

how the demand forecast and the slopes of the residual demand curves are associated with the day-ahead price premium. For the control variables in X_jht, we include firm-year-by-month fixed effects and hour fixed effects. We cluster the standard errors at the day of sample.

[Table 3]

Table 3 shows our regression results for equation (7). We begin by including only the demand forecast as our main independent variable. Column 1 indicates that an 1 percent increase in demand is associated with a 3 percentage point increase in the price premium. In column 2 and 3, we include the slopes of the residual demand curves from the day-ahead market and the first intra-day market. Consistent with our theoretical predictions in Result 3, we find that 1) more elastic residual demand in the day-ahead market are associated with a decrease in the price premium and 2) more elastic residual demand in the intra-day market are associated with a decrease in the price premium. Column 2 and 3 indicate that the direct effect of the demand forecast becomes weaken once we include the slopes of the residual demand curves. This is because the demand forecast is an indirect measure of market power, whereas the slopes of the residual demand curves are more explicit measures of the large firms' abilities to exercise market power.

Given the potential endogeneity of the slopes of residual demand, we instrument them with weather variables.[32] In particular, we use the hour of the day interacted with average temperature, maximum temperature and minimum temperature.[33] We present the results in column 5. We find similar signs on the slopes, consistent with our theory. Finally, we include wind forecast in columns 4 and 5. Large wind forecast implies that wind farms operate at closer to their generation capacities. This means that, if wind farms are major arbitragers, their arbitrage capacity is lower when there is more wind forecast. In addition, Result 5 suggests that the presence of wind output may attenuate the incentives to arbitrage, as wind farms become larger. For these two reasons, we expect a positive sign for the effect of the wind forecast on the day-ahead price premium. With day-of-sample fixed effects, we do not find a strong evidence of wind affecting the premium.[34]

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natural log of the intra-day market price: $\Delta p_h = \ln p_{h,DA} - \ln p_{h,IT}$.

[32]Note that the demand forecast is made publicly available to the firms before the day-ahead market, and it is therefore predetermined.

[33]Unfortunately, our weather data are only daily. We find similar sign effects if we include hour-by-month-of-sample fixed effects in the regression, to control for hour seasonality more broadly, although we substantially loose precision.

[34]Day-of-sample fixed effects take out substantial variation in wind patterns, which are quite correlated within a single day. With month-of-sample fixed effects, we find a positive effect of wind forecast on the premium, in line with our theory.

4.2 Evidence from Wind Farms and Portfolios

In the previous section, we find that 1) there is a systematic day-ahead price premium in the Iberian sequential electricity market, and that 2) market power appears to play an important role in creating the price premium. With such arbitrage opportunities, our theory predicts that fringe firms should have incentives to arbitrage. In section 3.3, we highlight that wind farms may have several advantages to be an arbitrager in this market. We explore if wind farms that are owned by the large dominant firms behave differently compared to those owned by fringe firms. We then turn our analysis to other generation technologies such as thermal and hydro power plants and examine if firms also use these technologies for leveraging arbitrage opportunities.

Aggregate Patterns We start by analyzing how firms update their positions (i.e. commitments to produce at a given hour) through sequential markets. The theoretical model predicted that fringe firms should engage in arbitrage, whereas dominant firms should have no incentive to arbitrage, and, more generally, an incentive to withhold output in the earlier markets. To show evidence from our raw data, we begin by presenting aggregate patterns for fringe and dominant firms. For notational simplicity, we use q^w for electricity generation from wind farms and Q for total electricity production from all types of power plants including wind, thermal, hydro, and others. Consider production from wind farms q^w. We aggregate unit-level quantity data into the total quantity for two groups: 1) fringe firms and 2) dominant firms, which include the four largest firms in the market—IBEG, ENDG, GASN, and HCENE.[35] For each of the fringe and dominant groups, we define the difference between their position at a given market and their final position by:

$$\Delta q^w_{ghtk} = q^w_{ghtk} - q^w_{ght,\text{final}}, \quad \text{with } g = \{\text{fringe}, \text{dominant}\}, \tag{8}$$

where q^w_{ghtk} is group g's position at market k ($k = 0, ..., 7$) for wind electricity delivery at hour h on day t, and $q^w_{ght,\text{final}}$ is a group's final position for wind output. Therefore, Δq^w_{ghtk} shows how much a group (either the fringe or the dominant group) oversells wind in market k compared to their final position. Similarly, we investigate how firms update their positions for Q, which is the total output from all types of power plants. We aggregate quantities from all types of power plants and create $\Delta Q_{ghkt} = Q_{ghkt} - Q_{ght,\text{final}}$, which shows how much a group oversells total output in market k compared to their final position.

We calculate the means of Δq^w_{ghtk} and ΔQ_{ghtk} for group g, hour h, and market k, during our sample period. Figure 4 shows the mean of Δq^w_{ghtk} in Panel A and the mean of ΔQ_{ghtk} in Panel B. For fringe wind

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[35]During our sample period, about 30 percent of wind generation came from the wind farms owned by the four dominant firms.

Panel A: Wind Farms
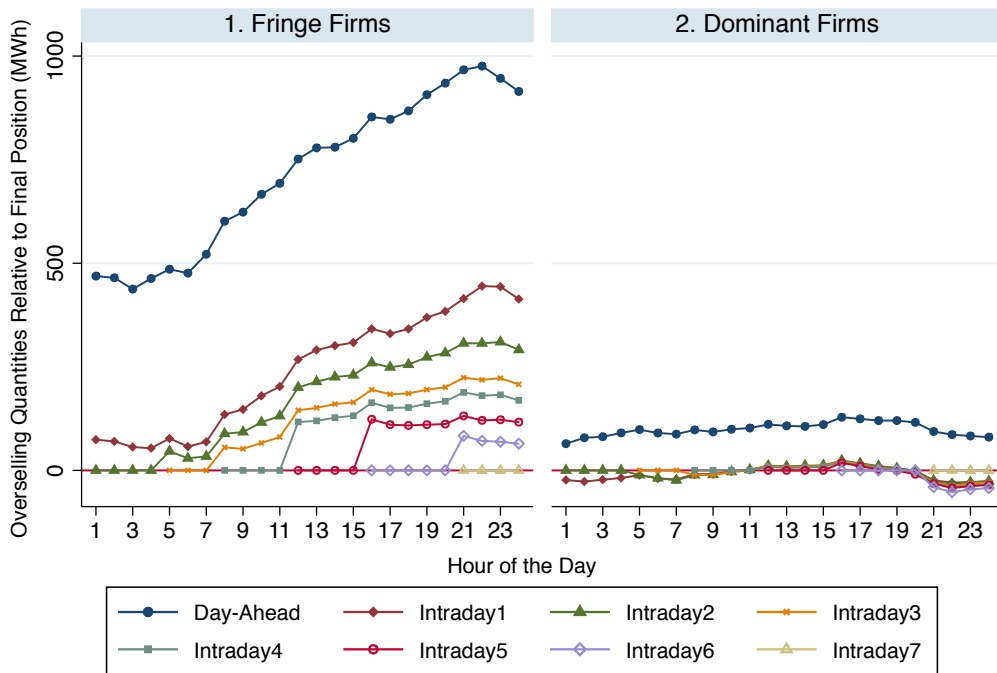
Panel B: All Power Plants
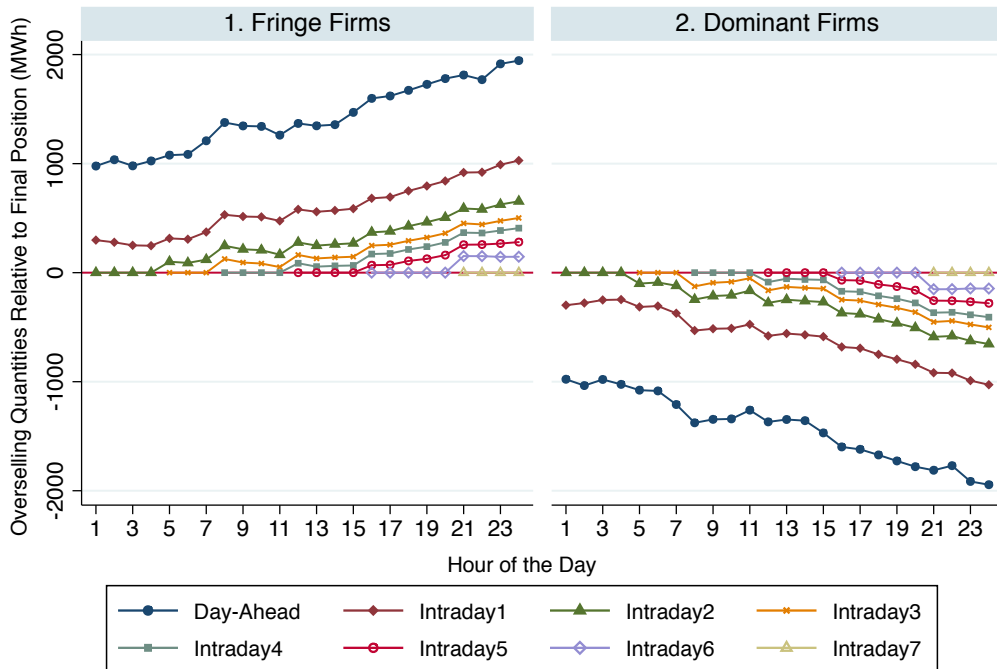
Figure 4: Systematic Overselling and Underselling in Forward-Markets Relative to Final Positions

Note: This figure shows average changes in fringe and dominant positions between a given market and their final commitment. Positive values imply that a group is promising more production than it actually delivers after all markets close.

farms, we find substantial overselling in the day-ahead and intra-day markets. They oversell in forward markets and gradually adjust their positions toward the final position through sequential markets. This gradual adjustment reflects the option values for adjusting their positions. This evidence is not an artifact of their portfolio composition because Panel B shows the same evidence for fringe firms' aggregate production, which include production from all technologies (ΔQ_{jhk}). On aggregate across production technologies, fringe firms commit to produce more energy at the forward markets (the day-ahead and earlier intra-day markets) than what they actually deliver.

The evidence is particularly compelling when we see the discontinuous differences in Δq_{jhk}^w between the sequential markets for hour 5, 8, 12, 16, and 21. These discontinuities are consistent with the market structure. For example, at hour 12, wind farms have five intra-day markets to update their positions. The overselling is largest at the first market and it decreases over time. Moreover, there is a discontinuous drop between the fourth and fifth markets. This is because firms have no more opportunity to correct their position after the last market. In the last market, they set their position nearly equal to their actual final production (i.e. $\Delta q_{jhk}^w \approx 0$).[36] In contrast, the overselling behavior is substantially different for hour 11. First, they do not oversell in the fourth market. This is because the fourth intra-day market is the last market for hour 11. Second, they oversell less in the first though the third markets for hour 11 compared to the amount of overselling for hour 12. This is because a smaller number of available markets for hour 11 leads to different option values in the forward markets.

We find notably different results for dominant firms. Panel A shows that there is almost no significant amount of overselling with wind by these large firms. The difference between their positions in the forward markets and the final production is much smaller than that for fringe wind farms. Furthermore, Panel B shows that dominant firms *undersell* in the forward markets with their overall portfolio. They withhold sales in the forward markets and sell more in the later markets, as suggested by our theory. This evidence is consistent with our theoretical prediction (Result 5)—large firms that exercise market power have significantly different incentives to arbitrage compared to the fringe firms' incentives.

One potential concern is that there is slight overselling by dominant wind farms for the day-ahead market. However, the nature of overbidding appears to be quite different, as it is flat across hours, while overselling by fringe wind farms appears to be correlated with the price arbitrage opportunities. The most likely reason for this behavior is the congestion market, which happens between the day-ahead and the first intra-day market. Dominant firms appear overstate wind production in the day-ahead market to reshuffle

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[36]Note that wind farms in this market have incentives to minimize the deviation between their final commitment quantity and their actual production because they have to pay "deviation prices" for such departures. Although we do not focus on their response to the deviation prices in this paper, we find evidence that wind farms generally respond to the incentive and minimize such deviations.

their production after the congestion market, even though in net they are withholding output, as shown in Panel B.[37] In fact, we see no overselling in all of the intra-day markets, which open after the congestion market. In the appendix, we present additional graphs, in which we show the position of each of the four biggest firms, both for wind farms and their overall portfolio. The graphs confirm that congestion induces substantial reshuffling across the dominant firms.[38] Yet, after congestion is controlled for, behavior in the intra-day markets is very consistent across firms, and in line with the predictions of our model.

Evidence from firm-level data The aggregate patterns provide strong evidence that fringe and dominant firms respond to the incentives in the sequential markets in a way that is consistent with our theoretical predictions. In this section, we analyze micro data at the firm level. Our theory suggests that the amount of arbitrage should be associated with predicted price premiums that are predicable from market fundamentals such as demand forecasts.

We test this hypothesis by using firm-level data by production technology such as wind, hydro, and thermal. Given that firms are very different in size, we examine log deviations. For each firm j, hour h and day t, we define the change in a firm's position from the day-ahead market to the first intra-day market with technology w by $\Delta \ln q_{jht,\mathrm{DA}}^{w} = \ln q_{jht,\mathrm{DA}}^{w} - \ln q_{jht,\mathrm{I1}}^{w}$. Similarly, we define the day-ahead price premium relative to the first intra-day market price by $\Delta p_{ht,\mathrm{DA}} = p_{ht,\mathrm{DA}} - p_{ht,\mathrm{I1}}$.[39]

Given that we would like to test if firms position changes are correlated with forecastable price differences at the time of bidding, we define predicted price premiums $\Delta \widehat{p}_{htk}$, with $k = \{\mathrm{DA}, \mathrm{I1}\}$, by regressing Δp_{htk} on the demand forecasts publicly available to firms, day-of-sample fixed effects, and, in some specifications, hourly fixed effects. The predicted price premiums therefore reflect the variation that can be predicted from these market fundamentals. The null hypothesis is that $\Delta \ln q_{jtk}^{w}$ is positively associated to $\Delta \hat{p}_{htk}$ for fringe firms, but not for dominant firms.

We estimate the following equation by OLS, separately for $\Delta \ln q_{jht,\mathrm{DA}}^{w}$ and $\Delta \ln q_{jht,\mathrm{I1}}^{w}$,

$$\Delta \ln q_{jhtk}^{w} = \alpha + \beta \Delta \widehat{p}_{htk} + \theta_j + \lambda_t + u_{htk}, \quad \text{with } k = \{\mathrm{DA}, \mathrm{I1}\}, \tag{9}$$

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[37] Importantly, the congestion market does not typically ration wind generation in itself, as it is given priority in the grid.

[38] Congestion is particularly relevant for GASN and ENDG. ENDG appears to be overselling with its portfolio, but this is because some of its power plants are in constrained regions. GASN, on the other hand, appears to massively undersell in the day-ahead market, which is again driven by congestion in the opposite direction. Unfortunately, these congestion patterns are very persistent, and therefore it is difficult to find a period with no congestion during our sample. Most of the flows in the congestion market are traded among these two firms, although IBEG and HCENE also experience some congestion events during the sample, which involve smaller amount of energy.

[39] We define the same variables for the change in the firms' positions and the price premium between the first intra-day market and the second intra-day market: $\Delta \ln q_{jht,\mathrm{I1}}^{w} = \ln q_{jht,\mathrm{I1}}^{w} - \ln q_{jht,\mathrm{I2}}^{w}$ and $\Delta p_{ht,\mathrm{I1}} = p_{ht,\mathrm{I1}} - p_{ht,\mathrm{I2}}$.

where β shows the percentage change in the arbitrage that is associated with one euro/MWh change in the predicted price premium. We include firm fixed effects θ_j and day-of-sample fixed effects λ_t.[40] In some specifications, we also include hourly fixed effects. We cluster the standard errors at the day of sample.[41]

Table 4 shows the regression results. We begin with Panel A, which shows results for wind farms that are owned by fringe firms. The estimate in column 1 implies that an one euro/MWh increase in the predicted forward-market price premium is associated with an increase in $\Delta \ln q_{jht,\mathrm{DA}}^w$ by a 0.088 percentage point. This is an economically significant increase given that the mean of the dependent variable is 0.134, as we report in the table.[42] In column 2, we include hour fixed effects. Note that hour fixed effects are likely to take some important variation out from the estimation because the price premium has systematic patterns by hour, and firms seem to respond to these systematic differences. Including the hour fixed effects absorbs these responses that are systematic to each hour, but it allows us to analyze if firms also respond to variation across days for a given hour. We find a smaller estimate (0.018) when we include the hour fixed effects. Still, this is estimated with small standard errors, which assures that we have consistent evidence even when we take variation across hours out of the estimation. In columns 3 and 4, we report the analogous results for $\Delta \ln q_{jht,\mathrm{I1}}^w$, which examines the overselling quantity in the first intra-day market relative to the second intra-day market. The estimates are smaller, but it is because the mean of the dependent variable (0.020) is much smaller than that for the day-ahed market. Overall, we find that fringe wind farms show both economically and statistically significant responses to price arbitrage opportunities.

In contrast, Panel B shows that wind farms that are owned by dominant firms have little responses to the price arbitrage opportunities. The point estimates are close to zero, and we cannot reject that they are statistically significant for most specifications.[43] This finding is notable because all wind farms have similar advantages to engage in arbitrage regardless of the ownership. In addition to wind farms, dominant firms have large generation capacities from other types of their power plants, such as thermal and hydro generation. They could, therefore, engage in arbitrage by using other technologies. We test this possibility in Panel C, in which we estimate the regression by using dominant firms' production from all types of their

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[40]We find that these fixed effects have almost no effects on the point estimates of β.

[41]We also estimate the standard errors for different levels of clusters. Clustering at the month of sample and at the week of sample produce very similar standard errors to our main results. A potential concern for clustering at the day of sample is that it may not adjust for potential serial correlation between observations within a firm. To examine this point, we estimate the standard errors using the two-way clustering at the day of sample level and at the firm level. We find that the two-way clustering makes little difference in the standard errors for our data.

[42]To interpret the magnitude of our estimates, it is also useful to report the distribution of the right hand side variables. For $\Delta p_{ht,\mathrm{DA}}$, we have -2.7 (p10), -0.42 (p25), 0.05 (p50), 2.56 (p75), and 5 (p90). For $\Delta p_{ht,\mathrm{I1}}$, we have -3.3 (p10), -1.14 (p25), 0 (p50), 1.55 (p75), and 3.95 (p90), all in euro/MWh. Therefore, considering "one euro/MWh increase" is reasonable given the variation in the price premium from the data.

[43]One exception is the day-ahead market regression with the hour fixed effects, in which we find a small effect (0.006).

power plants. We find the opposite effects. The negative signs for the estimates imply that we observe more *underselling* by dominant firms when there is an increase in the predicted forward-market price premium. This underselling or withholding behavior by dominant firms (firms that have market power) is consistent with the predictions from our theoretical model.

[Table 4]

Evidence from other production technologies   Finally, we explore if dominant and fringe firms engage in arbitrage by using other technologies by estimating equation (9) by production technology. Compared to wind generation, thermal and cogeneration plants have less flexibility to arbitrage, as their capacity constraints tend to be more binding. Furthermore, they might be more scrutinized by the regulator for systematic overselling in the forward markets. Traditional hydro power is flexible. However, most hydro reservoirs are owned by dominant firms.[44] Similar to wind, solar plants are also flexible and volatile. Yet, most solar plants do not participate in the intra-day markets and receive a flat tariff instead. Finally, market players in the demand side, such as retail electricity providers, possibly have flexibility to arbitrage, because their bids are not related to plant capacity, although this behavior is often discouraged.

Table 5 shows the results. We estimate the regression shown in column 3 in Table 4 for each type of power plants separately. Each estimate in this table comes from a single regression that includes particular type of fringe or dominant power plants. The dependent variable is the log difference in committed production quantity between the day-ahead market and the first intra-day market ($\Delta \ln q_{jht,\text{DA}}^{w}$). The independent variable is the predicted day-ahead premium relative to the price in the first intra-day market ($\Delta \widehat{p}_{jht,\text{DA}}$). All regressions include day-of-sample fixed effects, firm fixed effects, and hour fixed effects, as we do in in column 3) in Table 4. For fringe firms, we find overselling evidence by hydro and cogeneration plants, which is similar to the evidence from wind farms. We do not find statistically significant effects for other technologies. We report the estimates for dominant firms in the second row. We find no evidence of price arbitrage for all technologies: solar, hydro, cogeneration, thermal, and demand. Importantly, we find a statistically significant *negative* coefficient for dominant hydro plants and thermal plants. These estimates imply that dominant hydro and thermal plants respond to the forward-market price premium in the opposite direction, as compared to the responses by fringe firms that engage in price arbitrage.

[Table 5]

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[44]Fringe firms typically own small run-of-the-river hydro resources.

Summary   To summarize, we find strong evidence that fringe wind farms exploit foreseeable price differences and engage in profitable arbitrage, whereas dominant firms do not.[45] It is important to note, however, that we do not show that the amount of arbitrage is optimal, and certainly not enough to fully close the price differences. This fact could be explained by several reasons: transaction costs, institutional constraints on the amount of arbitrage (most likely of regulatory nature, as capacity constraints are usually not binding for wind, even with such levels of arbitrage), and strategic arbitrage.[46] We explore these hypotheses in the counterfactual section, by comparing the observed amount of arbitrage to the equilibrium levels under full arbitrage and strategic arbitrage.

5   Counterfactual Experiments

We find evidence that there is a systematic day-ahead premium in the Iberian electricity market, and that fringe wind farmers appear to arbitrage some of these differences away. How much does this behavior contribute to closing the price gap? What are the welfare implications?

Consider the simple example in Section 2 under two polar cases, one with no arbitrage (Result 1) and one with full arbitrage (Results 2). From the equilibrium analysis, it follows that the total quantity produced by the monopolist is lower when there is full arbitrage, as p_1 decreases, but p_2 increases. Given that p_2 determines the final allocation, the quantity produced by the monopolist is further away from the first best under full arbitrage. The intuition is that full arbitrage removes the ability of the monopolist to dynamically exercise market power across sequential markets. Under full arbitrage, the monopolist exercises relatively less market power in the first market, but more market power in the last market. These results suggest that introducing full arbitrage in this market is not necessarily welfare enhancing, as it reduces consumer costs at the expense of lower productive efficiency.

In this section, we quantify this trade-off between consumer surplus and productive efficiency. To do so, we construct a counterfactual model that allows us to empirically assess the interaction between market power and arbitrage. To make the counterfactual experiments empirically relevant, we extend the theoretical

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[45]We also find heterogeneity in arbitrage across fringe firms—some fringe firms engage in arbitrage more sophisticatedly than others. For each fringe firm, we calculate how much of their wind profit comes from arbitrage. Whereas this profit ratio is close to 0% for a half of the fringe firms, some firms gain considerable profit from arbitrage. The profit ratio is highest in hour 22—among 311 fringe firms, it is 2.2% for the firm at the 75th percentile and 7.1% for the firm at the 90th percentile. The profit ratio is systematically high in hours 19-24 and low in hours 1-5, constant with the overselling behavior we find.

[46]We find that capacity constraints are usually not binding for fringe firms that engage in arbitrage. Although they overstate their wind production in the day-ahead market, these overstated quantities usually do not reach their generation capacities. For each firm, we calculate the average ratio of the day-ahead quantity to the generation capacity. Among 311 fringe firms, the ratio is 23% for the firm at the 25th percentile, 28% for the firm at the median, 37% for the firm at the 75th percentile, and 58% for the firm at the 90th percentile. These statistics imply that firms could oversell even more in the day-ahead market. They do not oversell up to their generation capacities possibly because they may engage in strategic arbitrage or they may try to avoid regulatory scrutiny.

model to accommodate for several strategic firms, a flexible marginal cost function, and demand uncertainty.

5.1 Model for Counterfactual Simulations

We construct an empirical model to simulate the effects of alternative arbitrage policies in this market. The model extends the simple framework in several ways. We consider a model with two markets and N strategic firms that are playing a Cournot Nash equilibrium. Firms have capacity constraints. Each firm has a marginal cost curve that is piece-wise linear and continuous. The residual demand that the strategic firms face is also piece-wise linear. Demand in the second period is uncertain, with a commonly known distribution.

We solve the model by backward induction. In the real-time market, firms choose their optimal output levels given their previous commitments, which are the state variable of the game. We solve the last stage as a complementary problem, as in Bushnell et al. (2008), for a given quantity sold in the day-ahead market. For the cases in which there is arbitrage, firms take the amount of arbitrage as given. See Appendix B.1 for the equation details.

In the first stage, firms decide how much energy to sell in the day-ahead market, taking into account the strategic impacts to second-stage payoffs. We solve the optimal quantity in the first market with an iterated best-response algorithm in which firms are maximizing their joint profits between the first and the second market. See Appendix B.2 for the pseudo-code of the iteration.

We consider four different regimes for our simulations:[47]

- **Wind Arbitrage (Baseline):** We consider the case in which wind farms are arbitraging price differences by, on aggregate, overbidding 20% of their actual expected production. We do not take a stand on whether such 20% is optimal.

- **Full Arbitrage:** We consider the case in which there is full arbitrage. The arbitrageurs engage in arbitrage so that the price in the first market equals the expected price in the second market.

- **No Arbitrage:** We consider the case in which the oligopolists participate in sequential markets, and there is no arbitrage by wind farms. Fringe firms passively offer their production at marginal cost.

- **Strategic Arbitrage:** We consider the case in which there is an arbitrageur who is strategic. It maximizes its profit by extracting rents from arbitrage without fully closing the price gap. Limited arbitrage arises as an equilibrium outcome.

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[47]Appendix B details how these counterfactuals mathematically affect the simulation procedure.

We use data from the Iberian electricity market to validate the baseline model and assess the welfare implications of these various counterfactuals.

5.1.1 Dominant Firms

An advantage of analyzing firms' behavior in electricity markets is that we can obtain a reasonable estimate of the marginal cost of production at the generation unit level. We collect unit-level technology parameters, such as heat rates, from the regulatory report by the market operator. We also obtain daily fuel cost data for gas-, coal-, and oil-fired plants and nuclear power plants from the Bloomberg database. Using engineering cost functions for each type of units, we calculate the constant marginal cost for each unit for each day. Based on this procedure, we can construct an increasing step function of the marginal cost curve for each firm that includes their thermal and nuclear power plants.

There are a few important factors to be considered when constructing the marginal cost curve. First, we focus on the marginal cost curve of thermal and nuclear plants owned by dominant firms, taking production from other sources as given (hydro power, wind, and solar). The units included in our cost curve produce on average around 40% of all electricity generation in the market. Second, not all power plants are available for a given day. For example, a plant is unavailable when it has a scheduled maintenance. We exclude these units to create the marginal cost curves based on available units for a given day. Third, firms often have bilateral contracts in addition to their production through the centralized markets. Our data include bilateral contracts, which we take into account when building firms' marginal cost curves. We also account firms' production from other sources when computing their strategic position.

Finally, we make a simplifying assumption on congestion. As explained above, between the day-ahead and the intra-day markets, the system operator adjusts for the congestion by asking firms to change their production, which can give rise to local market power. Modeling the strategic incentives that arise from congestion, by endogenizing network flows in this market, is beyond the scope of this paper.

5.1.2 Fringe Supply and Residual Demand

Dominant firms optimize production in response to the residual demand curve. We approximate the residual demand curve from the data. Using the bidding data from fringe firms and the approach used in section 4, we obtain the residual demand curve for the largest four dominant firms. We then calculate b_1 and b_2, the slopes of the residual demand curves at the market clearing prices for the day-ahead market and the first intra-day market, respectively. It is important to note that our residual demand slopes take into account any elasticity coming from demand bids.

In order to estimate the demand intercept, A, we use day-ahead clearing prices and quantities. For a given day-ahead price p_{1t}, dominant production q_{1t}, and residual demand slope b_{1t}, we calculate $A_t = q_{1t} + b_{1t}p_{1t}$.[48] The resulting estimates of the term A cannot be directly interpreted. Rather, the term A is an auxiliary construct that allows us to fit the residual demand in a parsimonious way. In our approach, this approximation approach is valid as long as our counterfactuals are of local nature, so that the slope estimate for the residual demand is still meaningful.[49]

The empirical evidence from the previous sections shows that wind farms oversell in the day-ahead market. For our counterfactual analysis, we consider arbitrage as a shift in the residual demand curve. We assume that in the data, firms are overstating their wind output by 20 percent in the day-ahead market, based on actual wind output. In other counterfactuals, we investigate alternative market outcomes that endogenize the amount and nature of the arbitrage.

Finally, to model changes in forecasted demand between the day-ahead market and the forward market, we use the distribution of changes in expected demand minus expected wind production. We find that joint changes in forecasted demand and wind are roughly centered around zero, with a standard deviation of 200 MWh. We thus use a normal distribution with mean zero and standard deviation equal to 200. In the simulations, and in order to reduce computation time, we approximate such a distribution with 15 representative draws, which are weighted according to their densities.

5.2   Results

We present results from the counterfactual model for the period between January 2010 and December 2011.[50]

Baseline   We simulate the Cournot equilibrium for the case in which wind farms are overbidding. Figure 5 presents the day-ahead price distribution and day-ahead premium against the actual data. One can see that the model does a fairly good job at capturing the main patterns in the data. The price distribution is comparable to that observed in our data, in spite of missing some price spikes. The model also predicts a distribution of price premium that resembles the one in the data. The distribution shows that, in the presence of market power and limited arbitrage, a positive price premium can arise in equilibrium.

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[48]A similar approach is used in Bushnell et al. (2008).

[49]The computational model can be easily extended to incorporate a piece-wise linear demand, at only minor computing time costs. We have decided to keep the residual demand as locally linear so that our computational model closely matches the theoretical framework.

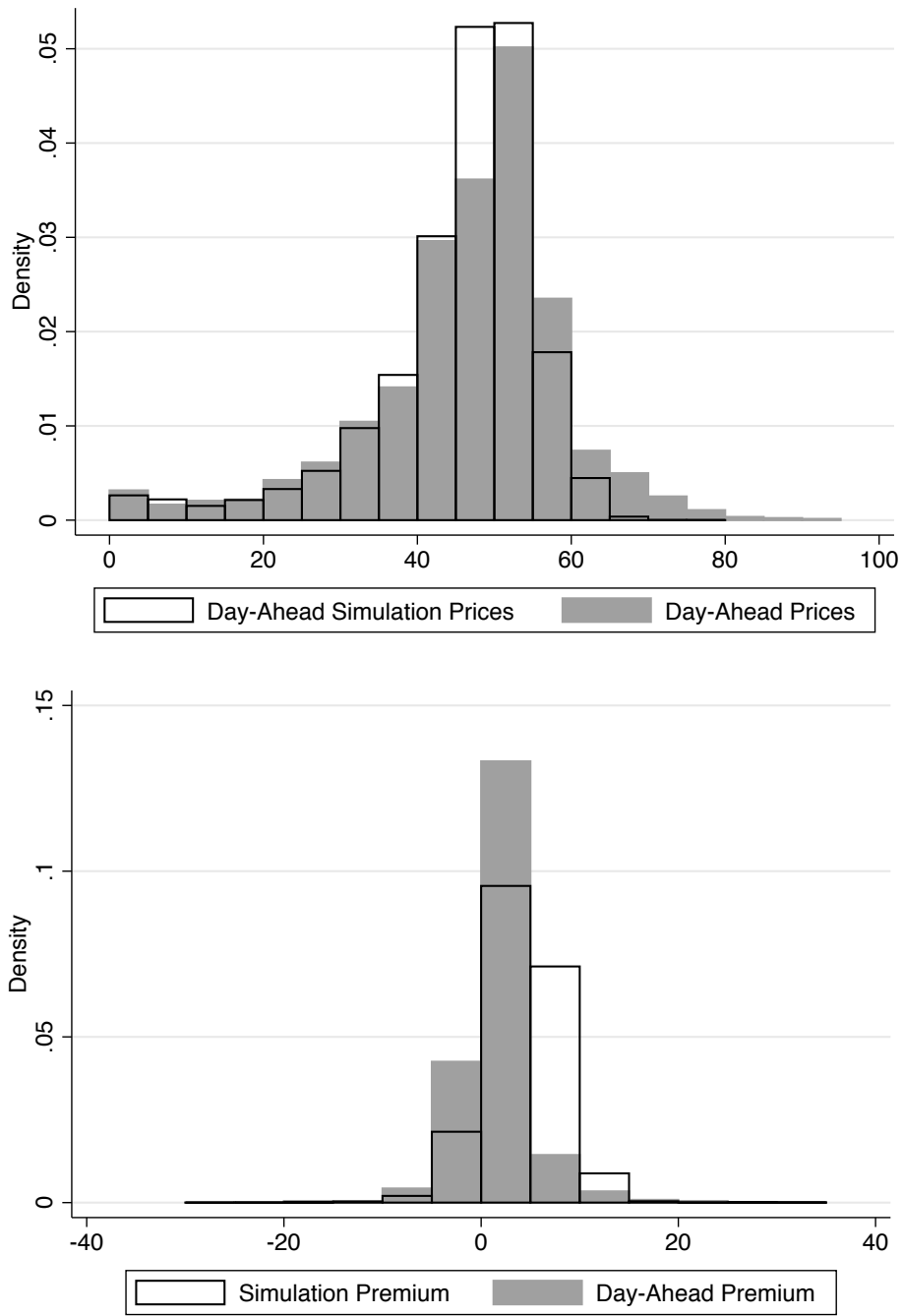[50]Our engineering cost estimates do not extend to 2012.

Figure 5: Baseline Simulation Results for $b_2 < b_1$
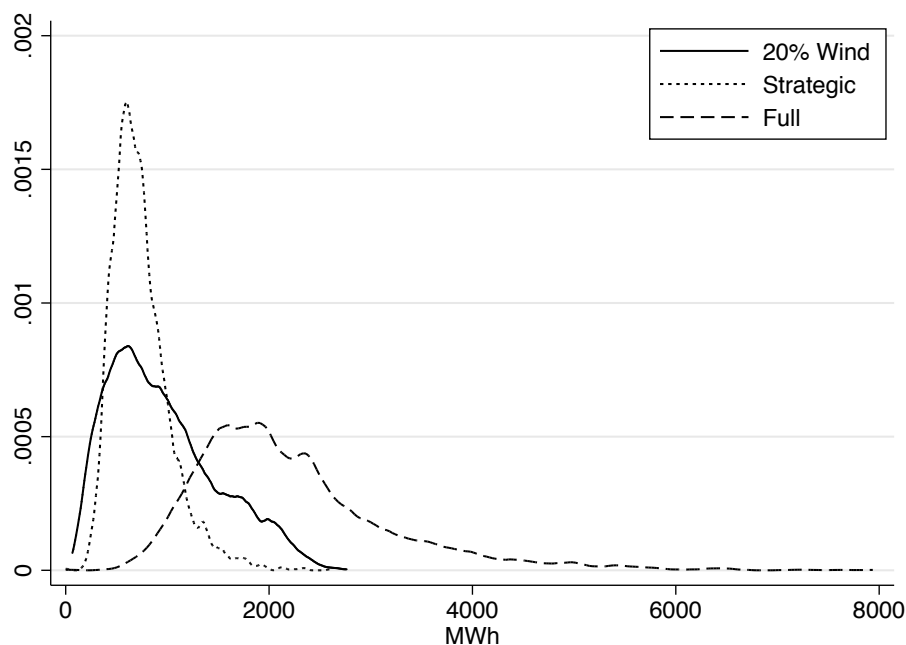
Figure 6: Strategic vs. Full Arbitrage for $b_1 > b_2$

Arbitrage   Our model computes arbitrage outcomes under several alternative hypothesis: 20% of wind production, strategic arbitrage and full arbitrage. Because a price premium is present in the market, we know that wind arbitrage is not full. Yet, how far is it from full arbitrage? How does it compare to the amount of arbitrage that a strategic arbitrager would do?

Figure 6 presents the distribution of arbitrage amounts under the different counterfactuals considered for the more realistic case in which $b_2 < b_1$. We observe that the observed amount of arbitrage in this market is larger than what a single strategic arbitrager would do, consistent with firms competing, to some extent, for these arbitrage opportunities. However, the arbitrage amount is much less than what would be needed for prices to converge. There are several potential explanations. First, such large amounts of arbitrage may be discouraged by the regulator. Second, whereas fringe firms engage in arbitrage, only a few sophisticated ones exploit the most profitable arbitrage strategies. As shown in the theoretical model, if only few firms participate in the market, they may have little incentives to fully close the price gap. In this sense, whereas arbitrage is not monopolistic, it might be far from perfectly competitive.

Comparison across Regimes   We compare the performance in terms of welfare under five different regimes— baseline, full arbitrage, no arbitrage, and strategic arbitrage, together with a spot-market-only counterfactual.

To measure welfare, a key variable is total production by the oligopolistic firms. Under most demand conditions, in equilibrium, there will be too little output from the strategic producers. In our model, demand is inelastic and fringe players produce at their marginal cost. Therefore, the social welfare can be improved when the strategic firms produce more. For each of the counterfactuals, we consider two cases: one in which the residual demand has the same slope in the second market ($b_2 = b_1$), and one in which the residual demand in the second market becomes less elastic ($b_2 < b_1$). As explained above, empirically, the residual demand tends to be less elastic in the second market.

Table 6 presents hourly averages for the counterfactual results. First, it is important to note that sequential markets, independent from the form of arbitrage, perform better than a single market. Prices tend to be lower in the presence of two markets, and total production costs (which include fringe costs) are also lower, by about 1%. This difference in performance is isolating the role of sequential markets in reducing firms market power, as pointed out by Allaz and Vila (1993).[51] Whereas 1% is not a very large number, electricity markets clear at every hour of the year, potentially implying annual cost savings of 80-100M €.

Conditional on having sequential markets, what is the role for arbitrage? For the case in which $b_1 = b_2$, one confirms the intuition from the simple framework. Full arbitrage closes the gap between $p1$ and $p2$, and results in the lowest $p1$ among the four regimes. Consumers benefit from the lowered price. Even though the hourly price reduction might seem small in levels, it represent a 5 to 6% saving. At the same time, however, arbitrage increases total production costs because the quantity produced by the strategic firms inefficiently goes down, due to increased withholding, although the effects are relatively minor. Strategic firms are substantially better off in the case of no arbitrage, as compared to the one with full arbitrage, as it allows them to extract more rents. Given the relatively small size of the productive inefficiencies, to the extent that reducing electricity costs is a goal in itself, one could interpret the results as suggesting that arbitrage has consumer benefits at a relatively minor welfare cost.[52]

[Table 6]

Once we incorporate stickiness into the adjustments that can occur in the real-time market ($b_2 < b_1$), the results are more nuanced. We find that full arbitrage performs similarly to a market with inefficient arbitrage by wind farms, or no arbitrage at all. The intuition is that sequential markets do not contribute substantially at approaching the first best, due to the limits on market expansion that occur in the second market. Strategic

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[51]In our model, we allow the single market to clear under best conditions (full information and responsive residual demand at b_1). Therefore, the differences are purely driven by attenuation of market power.

[52]From an environmental perspective, one could argue that electricity prices are already too low, making the reduction in prices not necessarily desirable.

firms anticipate those reshuffling limitations and withhold more output in the first market when full arbitrage is present. Because reshuffling is limited in the second market, strategic firms are better off by withholding output in a way that avoids a price drop in the first market. Given these anticipation effects, an important implication is that the reductions in consumer costs from full arbitrage are greatly attenuated.

Our results are also useful to think about the role of having a responsive secondary market (large b_2). Comparing the case in which $b_2 = b_1$ versus the case in which $b_2 < b_1$, one can see that sequential markets are most efficient at reducing market power when both markets are well participated. Whereas the productive efficiency effects are limited, the price effects are substantial, specially when full arbitrage is implemented. This suggests that arbitrage, as a measure to reduce consumer costs, will be most effective when fringe firms actively participate in both the day-ahead and the real-time markets.

Finally, it is important to discuss our assumptions on the costs and benefits of arbitrage in itself, which we assume to be zero. On the benefits side, we assume that arbitrage is not productive in itself. One could argue that arbitrage provides additional benefits, e.g. if arbitrageurs have better information, which could improve the counterfactual outcomes under full arbitrage. On the cost side, we assume that arbitrage comes at no additional cost, i.e., arbitrage is frictionless and entails no transaction costs.[53] Therefore, it is a best case scenario for arbitrage on the cost side. To the extent that arbitrage entails some real costs, the counterfactual welfare outcomes of full arbitrage would be worsened. Whereas modelling these elements is not the focus of our paper, it is important to keep in mind that they might increase or reduce the attractiveness of arbitrage in practice.

6   Conclusions

We study price differences in sequential markets. In the context of electricity markets, we find that a declining price path can arise in equilibrium under imperfect competition and limited arbitrage, even in the absence of other potential explanations playing a role, such as information updating or risk aversion. Empirically, we show that the price differences across sequential markets are correlated with traditional measures of market power, and can be interpreted as a lower bound on markups.

In the presence of these price differences, producers appear to engage in profitable arbitrage, specially with their wind farms. We show that the behavior observed at the firm-level is consistent with the hypothesis of market power. Wind farms that do not have substantial levels of market power exploit price differences

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[53] In practice, whether wind farms or financial agents perform the arbitrage can have real consequences (Jha and Wolak, 2014). In our setting, arbitrage by wind farms could generate dynamic inefficiencies, as the system operator is not planning for the right amount of wind production when assessing reliability constraints at the day-ahead market. Financial arbitrage, thus, could attenuate some of these distortions.

in these market. On the contrary, dominant firms that have market power underschedule production in the day-ahead market.

Finally, we analyze the interaction of arbitrage and market power with a counterfacual model. We find that market power and arbitrage are empirically relevant factors explaining the price premium. In our baseline counterfactual, we find a day-ahead premium distribution that is comparable to the one in the actual data. We also find that, holding the degree of market power unchanged, arbitrage does not necessarily have positive welfare effects in this market. For the case in which production can be easily adjusted, full arbitrage substantially reduces day-ahead prices, but at the expense of reduced productive efficiency.

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Table 1: Summary Statistics of Main Variables

	Mean	SD	P25	P50	P75
Price Day-ahead (p_1)	44.7	14.1	38.6	48.0	53.5
Price Intra-day 1 (p_2)	43.8	13.9	38.0	46.2	52.5
Day-ahead premium ($p_1 - p_2$)	0.9	4.0	-0.4	0.5	2.6
Average Slope of DA Res. Demand (b_1)	602.6	441.0	433.6	490.2	564.2
Average Slope of I1 Res. Demand (b_2)	103.2	108.8	72.4	87.1	103.1
Average Markup DA (q_1/b_1)	5.2	2.0	3.8	5.1	6.5
Average Markup I1 (q_2/b_2)	3.3	2.0	1.8	3.1	4.5
Demand Forecast (A)	29.3	5.2	24.8	29.4	33.3
Wind Forecast (q^w)	5.0	2.8	2.8	4.5	6.7

Note: Prices in Euro/MWh. Slopes in MWh/Euro. Demand and wind forecasts in GWh. Slope of residual demand computed for the four biggest firms in the market.

Table 2: Systematic Day-Ahead Price Premium

	pDA vs. pI1	pDA vs. pI2	pDA vs. pI3	pDA vs. pI4	pDA vs. pI5	pDA vs. pI6	pDA vs. pI7
Hour 1	0.00	0.00					
	[-1.01,2.21]	[-1.99,4.33]					
Hour 2	0.00	0.02					
	[-1.19,2.62]	[-2.05,4.49]					
Hour 3	0.00	0.00					
	[-1.44,2.51]	[-3.40,3.77]					
Hour 4	0.00	0.00					
	[-0.53,3.39]	[-3.00,4.65]					
Hour 5	0.10	0.00	0.00				
	[-0.11,3.23]	[-2.60,3.00]	[-3.52,4.11]				
Hour 6	0.00	0.00	0.00				
	[-0.52,3.10]	[-2.56,3.00]	[-3.64,3.51]				
Hour 7	0.50	0.00	0.00				
	[-0.01,3.18]	[-1.10,3.03]	[-2.00,3.95]				
Hour 8	0.55	0.00	0.00	0.00			
	[0.00,3.00]	[-0.90,2.92]	[-1.37,2.64]	[-2.70,4.17]			
Hour 9	0.00	0.00	0.00	0.00			
	[-0.48,2.05]	[-1.27,2.42]	[-1.30,2.56]	[-2.38,4.54]			
Hour 10	0.00	0.00	0.00	0.03			
	[-0.54,1.82]	[-1.08,2.27]	[-1.12,2.63]	[-2.00,5.37]			
Hour 11	0.00	0.00	0.00	0.80			
	[-0.76,1.73]	[-1.00,2.32]	[-1.00,2.81]	[-1.88,7.47]			
Hour 12	0.00	0.01	0.00	0.03	0.50		
	[-0.61,1.66]	[-0.76,2.28]	[-0.85,2.64]	[-1.00,3.44]	[-1.75,6.82]		
Hour 13	0.00	0.04	0.10	0.24	0.83		
	[-0.68,1.78]	[-0.82,2.48]	[-0.68,2.89]	[-0.97,3.53]	[-1.82,7.00]		
Hour 14	0.00	0.10	0.10	0.45	1.00		
	[-0.70,1.72]	[-0.62,2.34]	[-0.72,2.65]	[-0.97,3.64]	[-1.57,6.62]		
Hour 15	0.08	0.10	0.12	0.44	1.00		
	[-0.72,1.72]	[-0.59,2.29]	[-0.73,2.71]	[-0.73,3.56]	[-1.21,6.75]		
Hour 16	0.10	0.31	0.07	0.51	0.15	1.05	
	[-0.50,1.82]	[-0.46,2.37]	[-0.44,2.51]	[-0.55,3.34]	[-0.93,3.05]	[-1.70,7.29]	
Hour 17	0.47	0.50	0.29	0.90	0.33	1.12	
	[-0.15,2.00]	[-0.13,2.68]	[-0.21,2.82]	[-0.49,3.75]	[-0.60,3.41]	[-1.41,7.05]	
Hour 18	0.53	0.65	0.45	1.00	0.50	0.86	
	[-0.10,2.00]	[-0.19,2.68]	[-0.26,3.00]	[-0.34,3.96]	[-0.69,3.66]	[-1.67,6.50]	
Hour 19	0.75	1.00	0.74	1.00	0.50	0.45	
	[-0.01,2.35]	[-0.07,3.08]	[-0.09,3.11]	[-0.20,4.13]	[-0.75,3.72]	[-2.00,6.01]	
Hour 20	1.00	1.08	1.10	1.18	0.76	0.40	
	[0.00,2.90]	[0.00,3.85]	[-0.05,4.15]	[-0.20,4.86]	[-0.78,5.00]	[-2.12,6.78]	
Hour 21	1.06	1.43	1.39	1.50	1.12	0.52	0.54
	[0.00,3.00]	[0.00,4.18]	[0.00,4.70]	[-0.01,5.40]	[-0.33,5.00]	[-0.85,5.40]	[-1.83,8.13]
Hour 22	1.55	1.64	1.80	2.04	1.62	1.00	1.13
	[0.00,3.71]	[0.00,5.00]	[0.00,5.35]	[0.00,6.12]	[-0.10,5.43]	[-0.51,6.34]	[-1.62,8.64]
Hour 23	1.00	1.22	1.13	1.56	1.00	0.56	0.21
	[0.00,2.65]	[0.00,3.53]	[0.00,4.00]	[0.00,4.98]	[-0.27,4.23]	[-0.59,4.99]	[-1.57,6.71]
Hour 24	1.09	1.31	1.40	1.79	1.69	1.25	1.45
	[0.00,2.50]	[0.00,3.26]	[0.00,3.76]	[0.00,4.79]	[0.00,4.23]	[0.00,5.00]	[-0.40,7.01]

Note: This table shows the 25th, 50th, and 75th percentiles of the day-ahead price premium for each market by hours. We show the 25th and 75th percentiles in brackets below the 50th percentile. The distributions show that the day-ahead price tends to be larger than the prices in other markets, particularly during later hours of the day.

Table 3: Day-ahead Price Premium, Demand Forecast, and Slope of Residual Demand

Dependent variable: Day-Ahead Price Premium (Difference in Log Price)

	(1)	(2)	(3)	(4)	(5)
Demand Forecast (Log)	6.58	2.88	2.96	2.96	0.81
	(0.80)	(0.76)	(0.72)	(0.73)	(1.53)
Slope of Residual Demand in Day-Ahead Market (Log)		-3.52	-7.08	-7.07	-18.92
		(0.29)	(0.39)	(0.40)	(4.45)
Slope of Residual Demand in Intra-Day Market (Log)			4.41	4.41	15.87
			(0.30)	(0.30)	(4.80)
Wind Forecast (Log)				-0.03	1.92
				(0.14)	(0.74)
Observations	104580	104580	104500	104500	104292
Hour FE	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes
IV	No	No	No	No	Yes

Note: This table shows the estimation results of equation (7). The dependent variable is the day-ahead price premium in log. The standard errors are clustered at the day of sample. For the IV regression, we use average daily temperature, maximum daily temperature and minimum daily temperature interacted with the hour of the day to instrument the slopes at the day-ahead and intra-day market. Note that our weather data are only available until February, 2012, thus reducing the number of observations.

Table 4: Arbitrage by Fringe Firms and Dominant Firms

Panel A: Fringe Firms: Wind Farms
Dependent Variable: Arbitrage Quantities in Log

	Day-Ahead Market		First Intra-day Market	
Predicted Price Premium	0.088	0.018	0.013	0.006
(Euro/MWh)	(0.023)	(0.002)	(0.002)	(0.001)
Observations	6319354	6319354	6319354	6319354
Mean of Dep. Var.	0.134	0.134	0.020	0.020
Firm FE & Day FE	Yes	Yes	Yes	Yes
Hour FE	No	Yes	No	Yes

Panel B: Dominant Firms: Wind Farms
Dependent Variable: Arbitrage Quantities in Log

	Day-Ahead Market		First Intra-day Market	
Predicted Price Premium	0.014	0.006	0.002	-0.001
(Euro/MWh)	(0.010)	(0.002)	(0.001)	(0.002)
Observations	103772	103772	103772	103772
Mean of Dep. Var.	0.125	0.125	0.002	0.002
Firm FE & Day FE	Yes	Yes	Yes	Yes
Hour FE	No	Yes	No	Yes

Panel C: Dominant Firms: All Power Plants
Dependent Variable: Arbitrage Quantities in Log

	Day-Ahead Market		First Intra-day Market	
Predicted Price Premium	-0.219	-0.048	-0.022	-0.020
(Euro/MWh)	(0.066)	(0.007)	(0.004)	(0.004)
Observations	99009	99009	102124	102124
Mean of Dep. Var.	-0.154	-0.154	-0.083	-0.083
Firm FE & Day FE	Yes	Yes	Yes	Yes
Hour FE	No	Yes	No	Yes

Note: This table shows the estimation results of equation (9). For the day-ahead market, the dependent variable is the log difference in committed production quantity between the day-ahead market and the first intra-day market ($\Delta \ln q_{jht,\text{DA}}$). The predicted price premium is the predicted price differences between the day-ahead and the first intra-day market ($\Delta \hat{p}_{jht,\text{DA}}$). Similarly, the dependent and independent variables for the first intra-day market are $\Delta \ln q_{jht,\text{I1}}$ and $\Delta \hat{p}_{jht,\text{I1}}$ as defined in the text. Panel A shows the results for wind farms that are owned by competitive fringe firms. Panel B shows the results for wind farms that are owned by integrated incumbent firms, who also own other types of power plants such as thermal power plants. The standard errors are clustered at the day of sample. Panel C shows the results for dominant firms' total production from all types of power plants including thermal, hydro, and other plants.

Table 5: Arbitrage by Fringe Firms and Dominant Firms: By Power Plant Types

	Solar	Hydro	Cogen	Thermal	Demand
Fringe Firms	-0.008	0.005	0.007	-0.003	0.004
	(0.025)	(0.001)	(0.001)	(0.002)	(0.001)
Observations	389555	2359372	2106635	313664	2261250
Mean of Dep. Var.	-0.002	0.022	0.061	-0.005	0.040
Dominant Firms	0.004	-0.005	0.001	-0.023	-0.003
	(0.005)	(0.001)	(0.001)	(0.004)	(0.001)
Observations	56165	100257	101781	95847	103772
Mean of Dep. Var.	-0.008	0.001	0.005	-0.290	0.043

Note: We run the regression that is shown in column (3) in Table 4 for each type of power plants. Each of the twelve estimates in this table comes from a single regression that includes particular type of power plants. The dependent variable is the log difference in committed production quantity between the day-ahead market and the first intra-day market ($\Delta \ln q_{jht,\mathrm{DA}}$). The independent variable is the predicted price differences between the day-ahead and the first intra-day market ($\Delta \hat{p}_{jht,\mathrm{DA}}$). Each regression includes firm fixed effect, day-of-sample fixed effects, and hour fixed effects. The standard errors are clustered at the day of sample.

Table 6: Hourly Welfare Comparison Across Counterfactuals

	p_1 (E/MWh)	p_2 (E/MWh)	Premium (E/MWh)	Q_1 (GWh)	$Q_1 + Q_2$ (GWh)	Dominant Profit (000 Euro)	Total Costs (000 Euro)
Spot only (b_1)	-	45.0	-	0.0	13.6	207.7	793.2
Case $b_2 = b_1$							
Full Arbitrage	43.2	43.2	0.0	4.2	14.2	191.7	786.7
Wind 20%	46.2	40.2	5.9	11.9	15.4	219.7	783.3
No arbitrage	46.4	40.0	6.5	12.7	15.5	226.2	783.3
Str. arbitrage	45.8	40.7	5.1	10.8	15.2	221.8	783.5
Case $b_2 < b_1$							
Full Arbitrage	45.2	45.2	0.0	11.0	13.2	213.1	786.8
Wind 20%	45.3	41.2	4.1	12.2	13.4	212.5	786.8
No arbitrage	45.4	37.8	7.5	13.1	13.5	214.6	785.1
Str. arbitrage	45.3	40.4	4.9	12.4	13.4	214.6	785.5

Note: Welfare comparisons use sample of hours (8am, noon, 6pm and 9pm) during January 2010 to December 2011. Profits and costs represent average *hourly* costs. Profits are the sum of net profits across the four dominant firms. Total costs include both dominant firms production costs and fringe production costs.

Appendix

A Derivation of Equilibrium Strategies

A.1 Equilibrium without Arbitrage

Consider the case in which there is no arbitrage. At the second stage, the monopolist sets

$$p_2(p_1) = \frac{p_1 + c}{2}, \tag{A.1}$$

$$q_2(p_1) = b_2 \frac{p_1 - c}{2}. \tag{A.2}$$

From these expressions one can already see that, if the monopolist is a net seller in the first stage and $p_1 \geq c$,, then p_2 will be at most p_1.

At the first stage, optimal strategies imply,

$$p_1^* = \frac{2A + 2b_1 c - b_2 c}{4b_1 - b_2}, \tag{A.3}$$

$$q_1^* = \frac{(2b_1 - b_2)(A - b_1 c)}{4b_1 - b_2}, \tag{A.4}$$

$$p_2^* = \frac{A + 3b_1 c - b_2 c}{4b_1 - b_2}, \tag{A.5}$$

$$q_2^* = b_2 \frac{A - b_1 c}{4b_1 - b_2}. \tag{A.6}$$

Link to Result 1. We can use these expressions to show the results in Result 1. From the above expressions, one can see that the monopolist will be adjusting its quantity upwards in the second market as long as $A > b_1 c$, which is a necessary condition for q_1^* to be positive. Under the assumption that the monopolist is a net seller, it also implies that $p_1^* > p_2^*$, as $2A - 2b_1 c > A + 3b_1 c$. The forward premium is given by, $p_1^* - p_2^* = \frac{A - b_1 c}{4b_1 - b_2}$. The premium is increasing in A, decreasing in b_1 and increasing in b_2, showing the first and second part of Result 1. Looking at the special case of $b_1 = b_2$, the expressions of q_1^* and q_2^* simplify, and $q_1^* = q_2^*$. This implies that, if the forward and real-time market have the same elasticity, then the monopolist will sell the same amount of quantity in both markets. If $b_1 > b_2$ and the monopolist is a net seller (i.e., $A - b_1 c > 0$), $q_1^* - q_2^* = \frac{2(b_1 - b_2)(A - b_1 c)}{4b_1 - b_2} > 0$. This shows the third and fourth part of Result 1.

A.2 Equilibrium with Arbitrage

Now consider the case in which there is a competitive arbitrageur that can choose a quantity s to arbitrage between markets. We consider a Nash equilibrium in which the arbitrageur takes the actions of the monopolist as given, and the monopolist takes the actions of the arbitrageur as given.

Under the modified demands presented in (5) and (6), optimal strategies at the second stage imply,

$$p_2(p_1, s) = \frac{p_1 + c}{2} + \frac{s}{2b_2}, \tag{A.7}$$

$$q_2(p_1, s) = b_2 \frac{p_1 - c}{2} + \frac{s}{2}. \tag{A.8}$$

At the first stage, optimal strategies imply, for a given level of subsidy s,

$$p_1(s) = \frac{2A + 2b_1 c - b_2 c - s}{4b_1 - b_2}, \tag{A.9}$$

$$q_1(s) = \frac{(2b_1 - b_2)(A - b_1 c) - (3b_1 - b_2)s}{4b_1 - b_2}, \tag{A.10}$$

$$p_2(s) = \frac{A + 3b_1 c - b_2 c + \frac{2b_1 - b_2}{b_2} s}{4b_1 - b_2}, \tag{A.11}$$

$$q_2(s) = \frac{Ab_2 - b_1 b_2 c + (2b_1 - b_2)s}{4b_1 - b_2}. \tag{A.12}$$

The arbitrage level is given by the non-arbitrage condition $p_2(p_1, s) = p_1$. Setting p_2 equal to p_1 in equation (A.7), we obtain

$$s(p_1) = b_2(p_1 - c). \tag{A.13}$$

Using this equilibrium condition in expressions (A.9)-(A.12), we obtain

$$p_1^{**} = \frac{A + b_1 c}{2b_1}, \tag{A.14}$$

$$q_1^{**} = (b_1 - b_2)\frac{A - b_1 c}{2b_1}, \tag{A.15}$$

$$p_2^{**} = \frac{A + b_1 c}{2b_1}, \tag{A.16}$$

$$q_2^{**} = b_2 \frac{A - b_1 c}{2b_1}, \tag{A.17}$$

$$s^{**} = \frac{b_2(A - b_1 c)}{2b_1}. \tag{A.18}$$

Link to Result 2. From $q_1(s)$ and $q_2(s)$ it is clear that quantities in the first market are decreasing in s and quantities in the second market are increasing in s. Comparing p_1^{**} to p_1^* and p_2^*, one can check that p_1^{**} is smaller than p_1^* as long as $A - b_1 c > 0$, whereas p_2^* is lower than $p_1^{**} = p_2^{**}$. In particular, $p_1^{**} - p_1^* = -b_2 \frac{A - b_1 c}{8b_1^2 - 2b_1 b_2} < 0$, and $p_2^{**} - p_2^* = \frac{(2b_1 - b_2)(A - b_1 c)}{2b_1(4b_1 - b_2)} > 0$. The monopolist reacts to the arbitrage by lowering total quantity, and $q_1^{**} + q_2^{**} > q_1^* + q_2^*$. In particular, $(q_1^{**} + q_2^{**}) - (q_1^* + q_2^*) = -b_2 \frac{A - b_1 c}{8b_1 - 2b_2} > 0$, which completes the results.

A.3 Equilibrium with Limited Arbitrage

Now we include the restriction that $s \leq K$, i.e., there are some institutional constraints that limit the amount of arbitrage. As explained in the main text, the justification for such restrictions can be physical (power

plants cannot arbitrage more than their total capacity), or regulatory (large swings in production are typically discouraged). Taking the equilibrium value of s^{**} in the case with unlimited arbitrage, this implies that the constraint will be binding as long as,

$$K < \frac{b_2(A - b_1 c)}{2b_1},$$ (A.19)

in which case $s = K$. Otherwise, the equilibrium features full arbitrage and $s = s^{**}$. Whenever the constraint is binding, the equilibrium becomes,

$$\overline{p}_1^{**} = \frac{2 + bc - K}{3b},$$ (A.20)

$$\overline{q}_1^{**} = A - K,$$ (A.21)

$$\overline{p}_2^{**} = \frac{b_2(3b_1 - b_2)c + (2b_1 - b_2)K - A(b_1 - b_2) - b_1^2 c}{b_2(3b_1 - b_2)},$$ (A.22)

$$\overline{q}_2^{**} = \frac{(2b_1 - b_2)K - A(b_1 - b_2) - b_1^2 c}{3b_1 - b_2},$$ (A.23)

$$\overline{s}^{**} = K.$$ (A.24)

Link to Result 3. From the equations describing the capacity constrained equilibrium, one can see that, if K is binding, $\overline{p}_1^{**} > \overline{p}_2^{**}$, as $\overline{p}_1^{**} - \overline{p}_2^{**} = \frac{Ab_2 - b_1 b_2 c - 2b_1 K}{4b_1 b_2 - b_2^2} > 0$, whenever the constraint is binding. Trivially, the tighter the constraint K, the more often this will happen. From the constraint itself expressed in expression (A.19), we can also see that it is more likely to bind when A is larger. Taking derivatives with respect to b_1 and b_2, it is easy to check that the constraint is more likely to bind when b_1 is smaller and b_2 is larger.

A.4 Equilibrium with Strategic Arbitrage

We consider the case in which there is a single arbitrageur. Therefore, it is not optimal for the arbitrageur to close price differences, but rather to close them in an optimal way that maximizes its profits. We calculate the Cournot equilibrium between the monopolist producer (q_1, q_2) and the monopolist arbitrageur (s). The profit of the arbitrageur is given by,

$$\Pi^a = (p_1(q_1, s) - p_2(q_1, s))s,$$

where q_1 is taken as given and p_2 is implicitly defined by the equilibrium price in the second stage as a function of the first stage choices.

In the presence of strategic arbitrage (monopolist), the equilibrium becomes,

$$p_1^a = \frac{4Ab_1 + 2Ab_2 + 4b_1^2 c + b_1 b_2 c - b_2^2 c}{8b_1^2 + 3b_1 b_2 - b_2^2}, \tag{A.25}$$

$$q_1^a = \frac{\left(4b_1^2 - b_1 b_2 - b_2^2\right)(A - b_1 c)}{8b_1^2 + 3b_1 b_2 - b_2^2}, \tag{A.26}$$

$$p_2^a = \frac{3Ab_1 + Ab_2 + 5b_1^2 c + 2b_1 b_2 c - b_2^2 c}{8b_1^2 + 3b_1 b_2 - b_2^2}, \tag{A.27}$$

$$q_2^a = \frac{b_2(3b_1 + b_2)(A - b_1 c)}{8b_1^2 + 3b_1 b_2 - b_2^2}, \tag{A.28}$$

$$s^a = \frac{2b_1 b_2(A - b_1 c)}{8b_1^2 + 3b_1 b_2 - b_2^2}. \tag{A.29}$$

Link to Result 4. The price difference is given by $p_1^a - p_2^a = \frac{(b_1+b_2)(A-b_1 c)}{8b_1^2+3b_1 b_2-b_2^2} > 0$. Therefore, as in Result 1, the price premium is increasing in A and b_2, and decreasing in b_1. One can also see that price differences are smaller than in the case where no arbitrage is present, i.e., $p_1^a - p_2^a < p_1^* - p_2^*$.

A.5 Equilibrium with Wind Farms

Assume now that the strategic arbitrageur is producing q^w units of wind, which are exogenously given. The profit of the arbitrageur becomes,

$$\Pi^w = (p_1(q_1, q^w, s) - p_2(q_1, q^w, s))s + p_1(q_1, q^w, s)q^w,$$

where prices are now also affected by wind production.

The wind farmer has now a smaller interest to arbitrage, as arbitraging reduces the price received by wind production. Note that this formulation still allows the arbitrageur to set $s < 0$, in which case the wind farmer would be withholding output from the first market. In equilibrium,

$$p_1^w = \frac{4Ab_1 + 2Ab_2 + 4b_1^2 c + b_1 b_2 c - b_2^2 c - 4b_1 q^w}{8b_1^2 + 3b_1 b_2 - b_2^2}, \tag{A.30}$$

$$q_1^w = \frac{(4b_1^2 - b_1 b_2 - b_2^2)(A - b_1 c) + 2(2b_1^2 + 5b_1 b_2 - b_2^2)q^w}{8b_1^2 + 3b_1 b_2 - b_2^2}, \tag{A.31}$$

$$p_2^w = \frac{3Ab_1 + Ab_2 + 5b_1^2 c + 2b_1 b_2 c - b_2^2 c - 7b_1 q^w + b_2 q^w}{8b_1^2 + 3b_1 b_2 - b_2^2}, \tag{A.32}$$

$$q_2^w = \frac{b_2(3b_1 + b_2)(A - b_1 c) + b_2 q^w(b_2 - 7b_1)}{8b_1^2 + 3b_1 b_2 - b_2^2}, \tag{A.33}$$

$$s^w = \frac{2b_2(Ab_1 - b_1^2 c - 5b_1 q^w + b_2 q^w)}{8b_1^2 + 3b_1 b_2 - b_2^2}. \tag{A.34}$$

Link to Result 5. The price premium is still positive, as $p_1^w - p_2^w = \frac{(b_1+b_2)(A-b_1 c)+(3b_1-b_2)q^w}{8b_1^2+3b_1 b_2-b_2^2} > 0$. The price premium increases with A and q^w, and decreases with b_1. The premium increases with b_2 as long

	No Arbitrage	Full Arbitrage	Limited	Strategic	Strategic Wind
p_1	$\frac{2A+bc}{3b}$	$\frac{A+bc}{2b}$	$\frac{2A-K+bc}{3b}$	$\frac{3A+2bc}{5b}$	$\frac{3A+2bc-2q^w}{5b}$
p_2	$\frac{A+2bc}{3b}$	$\frac{A+bc}{2b}$	$\frac{A-2K+bc}{3b}$	$\frac{2A+3bc}{5b}$	$\frac{2A+3bc-3q^w}{5b}$
$p_1 - p_2$	$\frac{A-bc}{3b}$	0	$\frac{A-bc-2K}{3b}$	$\frac{A-bc}{5b}$	$\frac{A-bc+q^w}{5b}$
q_1	$\frac{1}{3}(A-bc)$	0	$\frac{1}{3}(A-bc-2K)$	$\frac{1}{5}(A-bc)$	$\frac{1}{5}(A-bc+q^w)$
q_2	$\frac{1}{3}(A-bc)$	$\frac{1}{2}(A-bc)$	$\frac{1}{3}(A-bc+K)$	$\frac{2}{5}(A-bc)$	$\frac{2}{5}(A-bc-\frac{3}{2}q^w)$
q_1+q_2	$\frac{2}{3}(A-bc)$	$\frac{1}{2}(A-bc)$	$\frac{2}{3}(A-bc-\frac{K}{2})$	$\frac{3}{5}(A-bc)$	$\frac{3}{5}(A-bc-\frac{2}{3}q^w)$
s	-	$\frac{1}{2}(A-bc)$	$\frac{1}{2}(3K-2A-bc)$	$\frac{1}{5}(A-bc)$	$\frac{1}{5}(A-bc-4q^w)$

Notes: Limited arbitrage case for the case in which the arbitrage capacity is binding, i.e., $K < \frac{1}{2}(A-bc)$.

as wind production is small enough, i.e., $q^w < \tilde{q}^w \equiv \frac{\left(5b_1^2+2b_1b_2+b_2^2\right)(A-b_1c)}{17b_1^2-6b_1b_2+b_2^2}$. Wind farm arbitrages price differences as long as it is small enough, i.e., as long as $s^w > 0$, which implies $q^w < \underline{q}^w \equiv \frac{b_1A-b_1c)}{5b_1-b_2}$. Otherwise, the farm will no longer arbitrage price differences, and behave as an oligopolistic producer instead, with an incentives to drive the premium up. The monopolist will contribute to the price premium as long as $q_2^w > 0$, which implies $q^w < \overline{q}^w \equiv \frac{(3b_1+b_2)(A-b_1c)}{7b_1-b_2}$. One can check that $\overline{q}^w - \underline{q}^w = \frac{\left(8b_1^2+3b_1b_2-b_2^2\right)(A-b_1c)}{35b_1^2-12b_1b_2+b_2^2} > 0$. One can also check that $\overline{q}^w - \tilde{q}^w = \frac{2(b_1-b_2)\left(8b_1^2+3b_1b_2-b_2^2\right)(A-b_1c)}{\left(7b_1-b_2\right)\left(17b_1^2-6b_1b_2+b_2^2\right)} > 0$, and $\tilde{q}^w - \underline{q}^w = \frac{(b_1+b_2)\left(8b_1^2+3b_1b_2-b_2^2\right)(A-b_1c)}{\left(5b_1-b_2\right)\left(17b_1^2-6b_1b_2+b_2^2\right)} > 0$.

A.6 Comparison for special case, $b_1 = b_2$

To gain some intuition on the comparative statics between regimes, it is useful to consider the simplified expressions for the case in which $b_1 = b_2 = b$. Table A.1 presents equilibrium prices and quantities for each of the cases considered. The table is useful to confirm some of the basic predictions of the model. First, one confirms that $p_1 > p_2$ for all equilibria considered, except for the case of full arbitrage, in which case $p_1 = p_2$. One can also see that, whenever positive, the premium is increasing in A, decreasing in b and increasing in q^w.

From the table, the price premium is largest in the absence of arbitrage, as long as q^w is sufficiently small. One can also see that the strategic arbitrageur reduces the price premium compared to the case of no arbitrage, but also that a strategic arbitrageur with wind production will have a lesser incentive to arbitrage. In this simplified example, the wind arbitrageur will have an incentive to arbitrage as long as $q^w < \frac{1}{4}(A-bc)$, i.e., as long as the wind farm is sufficiently small. As a point of comparison, the monopolist total production is $\frac{2}{3}(A-bc)$ in the case of no arbitrage and $\frac{1}{2}(A-bc)$ in the case of full arbitrage.

B   Computational details

B.1   Last stage: Capacity-constrained Cournot

We use a mixed integer solver to find the solution to the capacity-constrained Cournot equilibrium. The first order conditions can be expressed as a complementarity problem (Bushnell et al., 2008). We use an equivalent mixed-integer representation, and represent the first-order conditions as a set of constraints.

Assume market demand is $Q = A - bp$ in the day-ahead market. We observe Q, b and p in the data, and back out A to infer the intercept.[54] As in Bushnell et al. (2008), we model the marginal cost curve in piece-wise linear segments. For a given firm $i = 1, \ldots, N$, segment $j = 1, \ldots, J$, and quantity q $c_{ij}(q) = \alpha_{ij} + \beta_{ij}q$. Each segment has a maximum capacity $\bar{q}_{ij}$. Marginal costs are constructed so that the cost curve is continuous across segments, i.e. $\alpha_{ij} + \beta_{ij}\bar{q}_{ij} = \alpha_{ij+1}$. The model can also accommodate non-continuous, weakly increasing steps.

Define $\underline{u}$ and $\overline{u}$ a vector of dummies of length $N \times J$ that specifies whether a given step in the marginal cost curve is used at all ($q_{ij} > 0$), and whether it is used at full capacity ($q_{ij} = \bar{q}_{ij}$), respectively. Define $\psi_{ij} \geq 0$ as the shadow value when $\overline{u}_{ij}$ is binding. The equilibrium solves for the optimal vectors $\underline{u}, \overline{u}, \psi$, and q. In addition to the range conditions, the equilibrium conditions using a mixed integer formulation are as follows:

$$[\text{FOC 1}] \qquad P - \sum_J q_{ij}/b - \alpha_{ij} - \beta_{ij}q_{ij} - \psi_{ij} \leq 0 \qquad\qquad \forall i,j, \quad \text{(B.1)}$$

$$[\text{FOC 2}] \qquad P - \sum_J q_{ij}/b - \alpha_{ij} - \beta_{ij}q_{ij} - \psi_{ij} \geq M\underline{u}_{ij} - M \qquad\qquad \forall i,j, \quad \text{(B.2)}$$

$$[\text{Complementarity}] \qquad \psi_{ij} - M\overline{u}_{ij} \leq 0 \qquad\qquad \forall i,j, \quad \text{(B.3)}$$

$$[\text{Definition } \underline{u}] \qquad q_{ij} - \bar{q}_i\underline{u}_{ij} \leq 0 \qquad\qquad \forall i,j, \quad \text{(B.4)}$$

$$[\text{Definition } \overline{u}] \qquad \bar{q}_i\overline{u}_{ij} - q_{ij} \leq 0 \qquad\qquad \forall i,j, \quad \text{(B.5)}$$

$$[\text{Sorting 1}] \qquad \overline{u}_{ij} - \underline{u}_{ij} \leq 0 \qquad\qquad \forall i,j, \quad \text{(B.6)}$$

$$[\text{Sorting 2}] \qquad \underline{u}_{ij-1} - \underline{u}_{ij} \leq 0 \qquad\qquad \forall i, j = 2 \ldots J, \quad \text{(B.7)}$$

$$[\text{Sorting 3}] \qquad \overline{u}_{ij} - \overline{u}_{ij-1} \leq 0 \qquad\qquad \forall i, j = 2 \ldots J, \quad \text{(B.8)}$$

where P is implicitly defined as $P = A/b - \sum_{N,J} q_{ij}/b$, and M is a large value, e.g., $M = 10^6$.

The first condition establishes that marginal revenue is below or equal marginal cost. The second condition establishes that the marginal revenue equals marginal cost whenever a given step is used to produce. The third condition (Complementarity) establishes that the shadow value will only be positive if the step is binding, as it is the shadow value for capacity. This ensures that if a step is used to produce at an interior range, the FOC will be satisfied with equality and the shadow value will be equal to zero. The rest of the equations are used to define the auxiliary integer variables $\underline{u}$ and $\overline{u}$, as well as to establish the merit order in the supply curve.

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[54]The intercept is not directly interpretable. It is a way to ensure that our local approximation to demand is in the right range. Alternatively, the model can be adapted to have a full representation of the demand curve using a piece-wise linear approximation.

We use a mixed-integer solver (CPLEX) to find a solution to the first-order conditions.

Link to the dynamic model   The equations here are defined broadly for a capacity-constrained equilibrium. However, in our setting, the capacity-constrained equilibrium is the second stage of a dynamic game. Two key variables play a role: $\mathbf{Q}_1$ and s. $\mathbf{Q}_1$ represents the vector of committed quantities by each firm in the first stage. s determines the amount of arbitrage in the first stage. All these variables are pre-determined at this stage. $\mathbf{Q}_1$ affects the first order conditions as follows:

$$[\text{FOC 1 Dynamic}] \qquad P - \sum_J q_{ij}/b + Q_{i1}/b - \alpha_{ij} - \beta_{ij}q_{ij} - \psi_{ij} \leq 0 \qquad \forall i,j, \qquad (\text{B.9})$$

$$[\text{FOC 2 Dynamic}] \qquad P - \sum_J q_{ij}/b + Q_{i1}/b - \alpha_{ij} - \beta_{ij}q_{ij} - \psi_{ij} \geq M\underline{u}_{ij} - M \qquad \forall i,j, \qquad (\text{B.10})$$

i.e., it reduces the incentives of the firm to put markups, for $Q_{i1} > 0$..

The amount of arbitrage affects the equilibrium price, which is now defined as $P = (A + s)/b - \sum_{N,J} q_{ij}/b$, as the arbitrageurs buy back their commitments in the second stage, increasing the effective demand. In the simulations, we also allow for exogenous cost shocks to demand, so that $P = (A + s + \epsilon)/b - \sum_{N,J} q_{ij}/b$.

Finally, it is important to clarify how we accommodate for a different b in the second market. We calibrate the residual demand in the second market to go through the same point as the residual demand at the equilibrium price from the first market, absent any arbitrage. Therefore, we set A_2 such that $A_2 - b_2 p_1 = Q_1$. As explained above, A_2 is not directly interpretable, but it provides a convenient computational formulation to model local changes around the residual demand curve.

From the equilibrium price and quantities, we can compute the profit of each firm,

$$\Pi_{i2} = P\left(\sum_J q_{ij} - Q_{i1}\right) - \sum_J \left(\alpha_{ij} + \beta_{ij}\frac{q_{ij}}{2}\right) q_{ij}$$

Impact of counterfactuals on last stage   The main effect of the different counterfactuals is on the amount of arbitrage s. In the no arbitrage case, $s = 0$. In the wind arbitrage (baseline case), $s^w = 0.20q^w$. In the strategic arbitrage case, $s = s^m$, where s is given by the solution in the first stage where the arbitrageur maximizes profits. Finally, the full arbitrage case sets $s = s^{**}$, such that $p_1 = E[p_2]$, and is also determined in the first stage. Importantly, for the purposes of the last stage, s is sunk and given by the first stage.

B.2   First stage: Gauss-Seidel iteration

The pseudo-code in Algorithm 1 describes the iteration procedure, which is a standard Gauss-Seidel procedure that iteratively calculates the best response of each firm until no firm finds a profitable deviation. To define the profit of the firm when computing a best-response, we consider the case in which there is uncertainty being realized between the forward and the real-time market. Therefore, it is an expected profit over several realizations of uncertainty.

Algorithm 1 First stage iteration

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   procedure CournotDynamic
      $guess \leftarrow$ zeros(N,1)
      $crit \leftarrow 1000.0$
      $iter \leftarrow 1$
      while $iter < maxiter$ & $crit > tol$ **do**
         $oldguess \leftarrow guess$
         for $n = 1 : N$ **do**
            $guess(i) \leftarrow argmax_{q_i} \sum_\epsilon \Pi_i(q_i, guess_{-i}, s, \epsilon)$
         end for
         $crit \leftarrow \parallel guess - oldguess \parallel$
         $iter \leftarrow iter + 1$
      end while
   end procedure

Define a firm's profit as,

$$\Pi_i(q_i, q_{-i}, s, \epsilon) = p_1(q_i, q_{-i}, s) + \Pi_{2i}^*(q_i, q_{-i}, s, \epsilon),$$

where $\Pi_{2i}^*(q_i, q_{-i}, s)$ is the equilibrium profit in the second stage when q_i, q_{-i}, and s are played in the first stage. The differences across counterfactuals come from the amount of arbitrage. As explained above, $s = 0$ in the case of no arbitrage, and $s = 0.20q^w$ for the case of wind arbitrage. The strategic arbitrage case and the full arbitrage case need to solve endogenously for the amount of arbitrage. In those cases, the algorithm is expanded to also compute the best response for the arbitrageur (who maximizes profits in the strategic case, and equalizes prices in the full arbitrage case). This is implemented adding a fifth firm to the iteration procedure, who is either maximizing arbitrage profits or equalizing prices, taking the actions of the other players as given. The vector *guess* in the algorithm is modified to be of size $N + 1$. The algorithm stops when both firm quantities and arbitrage have converged.[55]

C   Additional Figures and Tables

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[55]We have examined the properties of the algorithm, and we have found that the algorithm converges smoothly in few iterations (typically less than 10). We have also examined the possibility of multiple equilibria both at the second stage and the first stage using some new tools that we are concurrently developing (Reguant, 2014), and we have not found evidence of multiple equilibria.
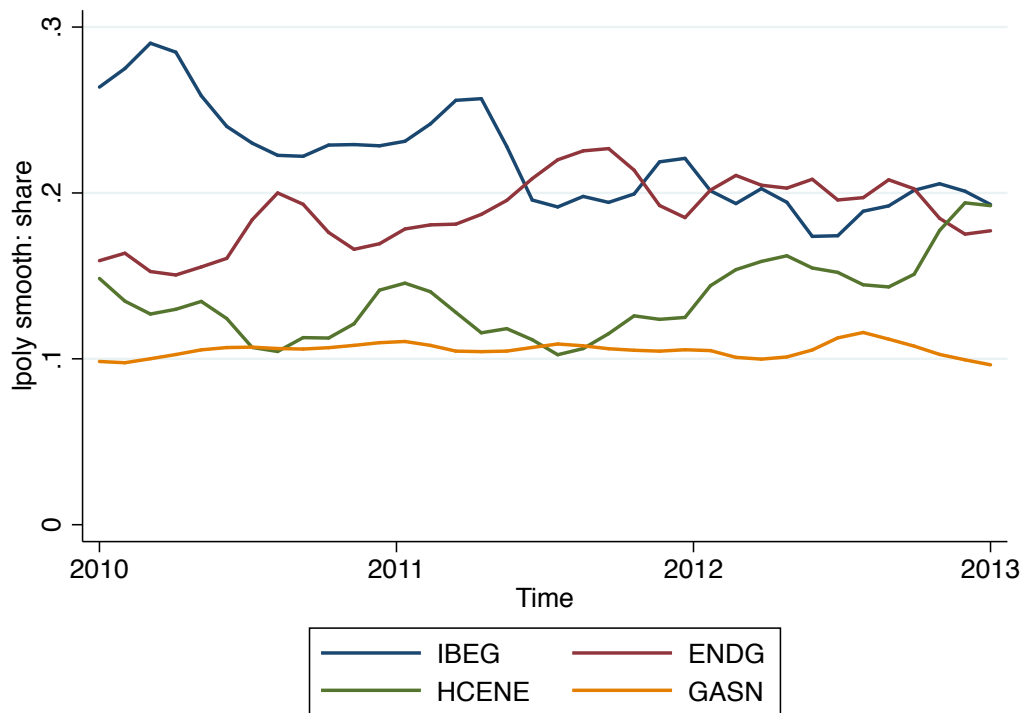
Figure C.1: Market Share of the Four Biggest Producers Over Time

Note: This figure shows the evolution of market share by the four biggest producers. As one can see, there are some fluctuations over time, which are driven by seasonality in electricity demand and hydro power, as well as changes in input costs, given that each firm has a different composition of power plants.
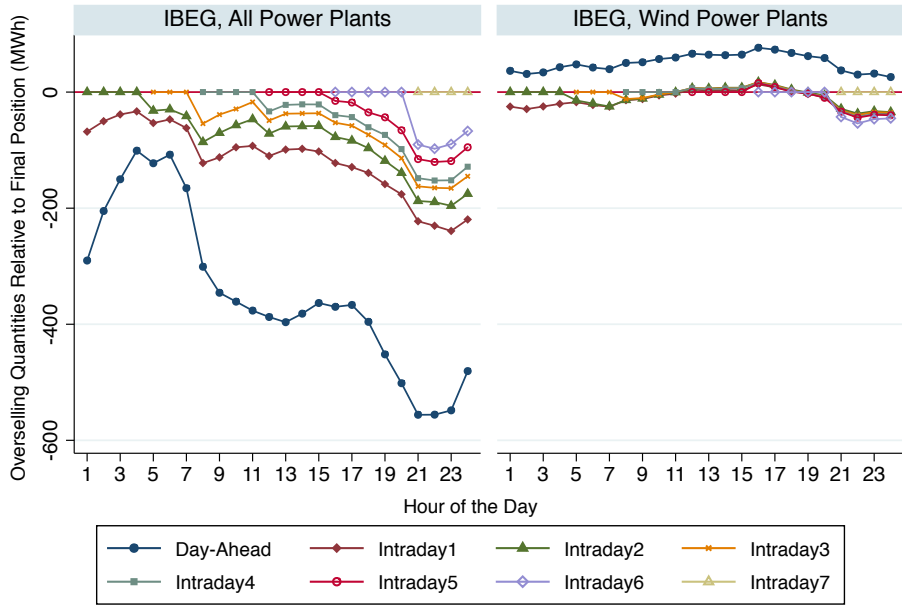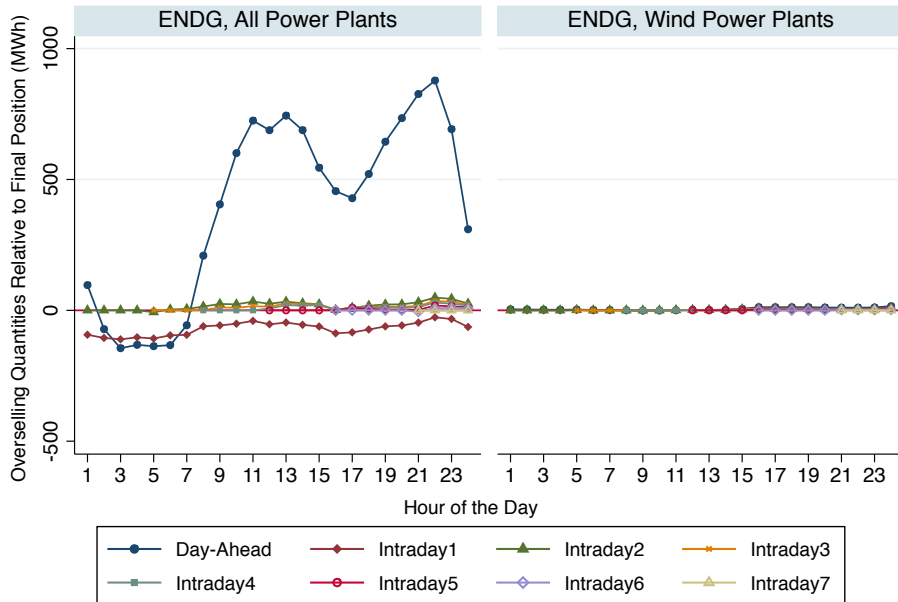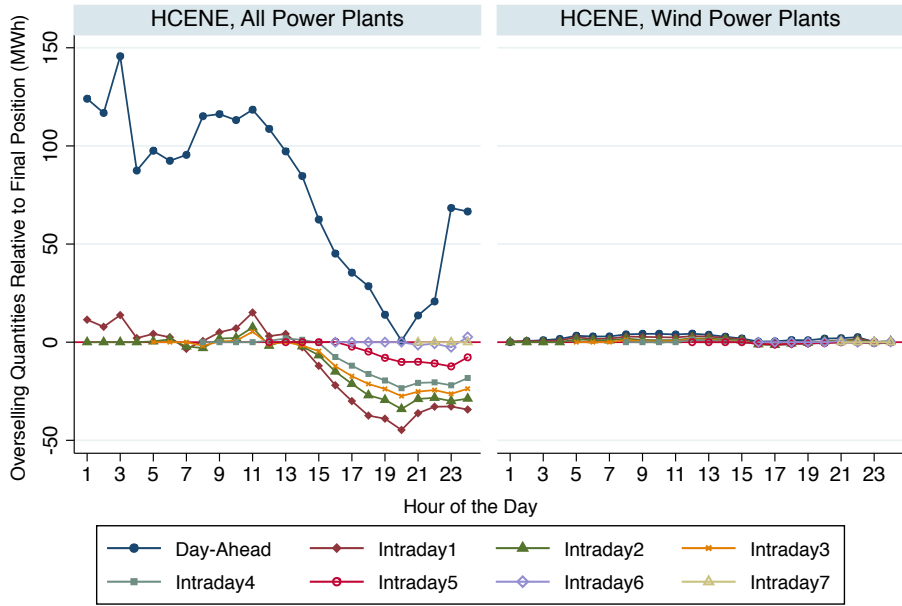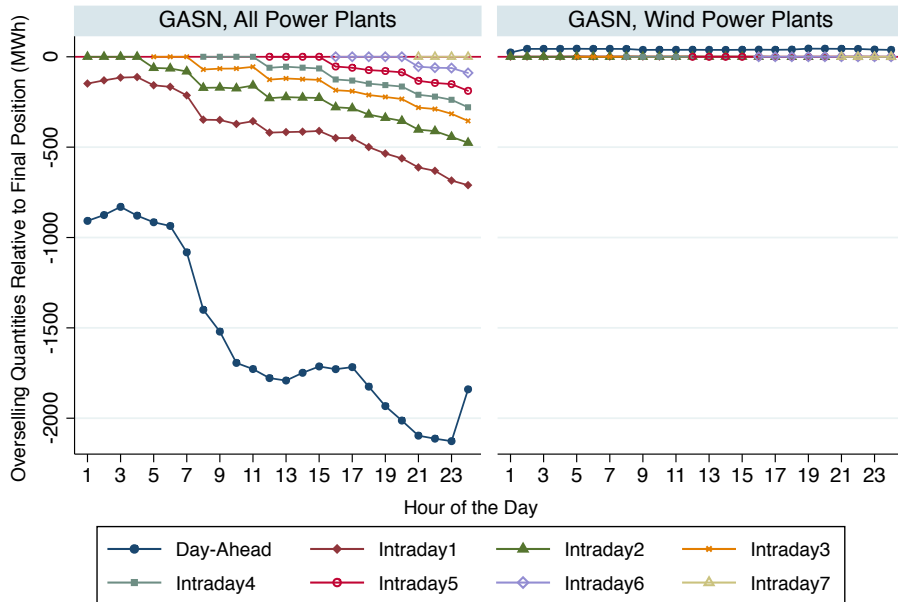
Figure C.2: Overselling and Underselling Relative to Final Positions (in MWh) by Each Dominant Firm

Note: This figure shows average changes in a firm position between a given market and a firm's final commitment. Positive values imply that a firm is promising more production than it actually delivers after all markets close.

Figure C.3: Overselling and Underselling Relative to Final Positions (in MWh) by Each Dominant Firm

Note: This figure shows average changes in a firm position between a given market and a firm's final commitment. Positive values imply that a firm is promising more production than it actually delivers after all markets close.